



**Università
degli Studi
di Palermo**

Ph.D. Program in Health Promotion and Cognitive Sciences

Sport and Exercise Sciences Research Unit

Department of Psychology, Educational Science and Human Movement

TRAINING LOAD AND PHYSICAL PERFORMANCE ANALYSIS IN SOCCER: A MACHINE
LEARNING APPROACH

PhD Coordinator

***Professor* GIUSEPPA CAPPUCCIO**

PhD student

***Dott.* GUGLIELMO PILLITTERI**

Supervisor

***Professor* GIUSEPPE BATTAGLIA**

Co-supervisors

***Professor* FILIPE MANUEL BATISTA CLEMENTE**

***& Professor* HUGO SARMENTO**

PhD CICLE XXXVI

Academic Year 2024/2025

INDEX

Abstract
Acknowledgements
List of abbreviations
List of table and figures

Chapter I - Introduction

1.0 An Updated Conceptual Framework on Physical Performance and Training in Soccer. A narrative review
2.0 Injury in soccer: from risk factors to prevention strategies
3.0 Implication of Machine Learning in soccer
4.0 Aims and Objectives of the thesis

Chapter II – Understanding soccer Physical Performance and Training Load

2.0 Chapter II overview
2.1 Toward a New Conceptual Approach to “Intensity” in Soccer Player’s Monitoring: A Narrative Review
2.2 Translating player monitoring into training prescriptions: Real world soccer scenario and practical proposals
2.3 Discussion

Chapter III - The relationship between Training Load and Training Outcomes in soccer: a Machine learning approach

3.0 Chapter III overview
3.1 Relationship between external and internal load indicators and injury using machine learning in professional soccer: a systematic review and meta-analysis
3.2 Association between match-related physical activity profiles and playing positions in different tasks: a data driven approach
3.3 Elite Soccer Players' Weekly Workload Assessment Through a New Training Load and Performance Score
3.4 Machine Learning Analysis of Intensity Profiles and Key Indicators in Standard Microcycle of Professional Soccer Players
3.5 Association between internal load responses and recovery ability in U19 professional soccer players: A machine learning approach
3.6 Training load and injuries prediction
3.7 A New Conceptual Framework for Managing Hamstring Injury Risk In Soccer – Implementing A Data-Informed Approach: A Brief Review

3.8 Discussion

Chapter IV - Personal skills and achievements

4.0 Learning experiences and skills at the Sport and Exercise Sciences Research Unit

4.1 Learning experiences and skills at Palermo FC

4.2 International period and international collaborations

4.3 Other published papers

Chapter V - Conclusion

5.1 Conclusion

5.2 Limitation

5.3 Practical application

References

Appendix

1. Articles under review
2. Co-authored abstracts
3. Co-supervised master thesis

Abstract

Training load monitoring represent a “on-field” common practice to optimize soccer training prescription aiming to enhance physical performance trying to reduce the injury risk. Understanding both external load, considered as the physical work prescribed in the training plan (e.g., measures of total distance covered (or in specific speed bands), accelerations, or metabolic power and internal load (i.e., the athlete’s physiological response to a given external load performed), offer a necessary practitioners’ support in informed-making concerning the training prescription. Worth noting, in order to prescribe optimal training (i.e., balancing the training dose and recovery,) to reach the desired adaptation, whole components of soccer performance must be considered such as training and recovery aspects, the athlete’s fitness status (i.e., physiological assessment), keeping into account the training methodologies principles as well as the match-day target derived from microcycle schedule. Several studies have been dealt with training load monitoring, physical performance, and injury risk reduction in soccer. The “era” of Big Data, is strongly characterized by the need to analyse a huge amount of data daily collected through Micro Electro-Mechanical Systems (MEMS) devices such as Global Positioning System, GPS and Inertial Measurement Unit, IMU as well as Heart Rate (HR) monitor devices or subjective scale (e.g., Rating of Perceived Exertion, RPE scale). Since traditional statistic methods result poor appropriate to reach this propose, the role of Artificial Intelligence (AI) and its daily application is spreading widely in many areas of the development sector including sports science. In the latter field, Machine learning (ML) is a branch of AI and computer science that focuses on the using data and algorithms to enable AI to imitate the way that humans learn, gradually improving its accuracy. In this context, especially in soccer, ML has been increasingly employed aiming to predict injury as well as to understand specific performance aspects. Relevant aspects such as the relationship between training load monitoring and training outcomes such as physical performance, recovery ability, training prescription and injury risk reduction should be yet better established and clarified aiming to provide an evidence-based consensus about strategies in a real word scenario as well as theoretical and methodological aspects in scientific community. Specifically, the difference between training drills and official match as well as an in-depth understanding of the external load profile of the playing position during different soccer activities and tasks, has not yet been provided through the machine learning approach. For these reasons, the overall aim of this thesis is to further the current understanding around the training load monitoring, physical performance and training prescription, focusing on the implication of machine learning on training load, physical performance analysis, and injury risk in soccer players. With this purpose, we tried to deeply understand the complex relationship between training load and training outcomes such as physical performance and injury risk.

We addressed over the course of three experimental chapters, which set out to achieve the following objectives:

This thesis attempts to provide a theoretical and practical contribution based on the gaps identified in the literature. Accordingly, the main research will answer relevant research questions as follow;

- 1) How practitioners can assess training load (including both intensity and volume) considering the differences between training and competition for each playing position aiming to support the training prescription process?
- 2) How can machine learning be implemented to understand the relationship between training and competition taking into account playing position to enhance physical performance and reduce injury risk?

Through 3 experimental chapters we addressed the main research questions.

Chapter 1 includes a narrative review with conceptual framework on physical performance and training in soccer, reporting an overview on injury in soccer and machine learning principles.

Chapter 2 offers 2 narrative review, the first one delves into the intensity concept, providing definition and insights, while the implication of player monitoring on training prescription has been explored in depth in the second work.

The relationship between training load and training outcomes considering machine learning approach has been reported through chapter 3. In detail, the chapter opens with a systematic review that deals with the relationship between external and internal load indicators and injuries based on machine learning approach. The chapter, through 4 original studies, has deepened the implications of ML on soccer training; the first study has offered relevant insights regarding the difference between match and drills, focusing on the target, intensity and the difference for playing position. In the second study, 2 scores were calculated with a ML approach, investigating the trend of this score in the microcycles. The third study investigated the difference in intensity between the MD typologies in a standard microcycle, considering the differences in playing position. The fourth study explores the intricate relationship between training load and recovery. Across all the studies, machine learning (ML) has demonstrated its value as a powerful tool for managing large datasets and uncovering relationships between complex, non-linear phenomena, such as training load and performance outcomes. This approach has provided fundamental insights, paving the way for promising future applications in understanding and optimizing these multifaceted dynamics.

Acknowledgements

My first recognition and gratitude goes to Professor Giuseppe Battaglia, my PhD tutor on this tortuous path who has constantly supported and advised me. He gave me the freedom to follow my passion and my area of interest and expertise, also involving me in other stimulating projects that have contributed to my human and professional growth.

Machine learning-based analysis requires knowledge of a complex "language" that requires experts in the field with "out of the ordinary" analysis skills. I would never have been able to deal with machine learning during my doctorate without the fortune of having met a person who gave me great support in several works carried out. Thanks, Alessio Rossi, a kind and helpful person with unique (computer science) skills.

A special thanks goes to Professor Filipe Manuel Clemente, who guided me throughout almost the entire process, both before and after the period abroad in Portugal where I was able to appreciate his undisputed human and professional qualities. Filipe, with whom a friendship was born, represents for me a model to follow in the field of research. His great organizational skills, his immense availability and reliability in providing all possible support were necessary to increase the quality of my work as well as fundamental for my professional growth. I would like to thank my supervisor during the period abroad, Professor Hugo Sarmiento, who was kind and helpful and supported me during this fantastic and stimulating period.

I am also extremely grateful to my friend Mohammad Izadi who has always supported me since the beginning of this fantastic journey (along with my colleague Salvatore Ficarra and professors Ewan Thomas and Valerio Giustino). His precious advice supported me in the early stages of the journey where it is necessary to orient oneself among the many difficulties. His motto "just search" contains a fundamental skill in the professional field and in life: the problem solving. My numerous requests and curiosities have been directed towards the search for greater autonomy in problem solving. In the same way, I want to thank my childhood friend Francesco Lunetta (Software Engineering Manager-Microsoft), a real human "genius." The continuous comparison with him has helped me to grow professionally, both in the field and in research.

To my UniPa professors: thank you for teaching me that learning every day keeps me alive. In particular, I would like to thank Professor Antonino Bianco, the undisputed leader of "motor sciences" who has always shown me great availability in the complex dynamics of submissions and "publications". His international network of acquaintances has been important to increase the exchange with different cultures in Europe. A hard-worker and workaholic, he represents a model to follow to achieve important goals in life. Thank you, professor Marianna Bellafiore, for involving me in different projects. Thanks to Professor Antonio Palma who gave me a great opportunity in life.

My family of origin also deserves my gratitude for this work: they probably don't know what I do specifically every day, but I couldn't have achieved certain goals without their support. Thank you, Grandma Sara, Mom, Dad, Amedeo, Ginevra. I apologize instead to my current family, Giuditta, my partner and mother of Elena, Sofia, Giulio, and my dog Spirit from whom I took so much time to dedicate to my work. I do not know to what extent you believe me but I do it daily for you and then for myself.

Thanks to Palermo FC, for 9 years it has given me the opportunity to work in an elite context as a physical trainer and sports scientist. I have collected a significant amount of data that has given me

the opportunity to continue my research activity. I have met many people and professionals of the highest level who have enriched my skills in this area. Thanks to Professor Marco Petrucci, Giuseppe Puleo, Tindaro Bongiovanni first and foremost and to all the staff and players with whom I have had the privilege of working.

Thanks to all the researchers and co-authors who have substantially contributed to the realization of my works by raising their quality. In particular, I am proud to have received the precious support of great researchers such as: Marco Beato, Carl Foster, Tim Gabbett, Judd Kalkhoven.

Last but not least: thanks to the PhD coordinator and the commission.

To conclude: thanks to the people who brought me down, especially as a child. those who didn't believe in me, who wouldn't have “bet a cent”, who only saw a child who was "difficult!" to manage because he was full of energy. I transformed some of the humiliations I suffered into positive energy, desire to do and maybe yes, passion and obsession.

There can be no worthy life without thanking the people who deserve it.

List of abbreviations

Abbreviations list	
TL	Training Load
EPTS	Electronic Performance and Tracking Systems devices
GPS	Global Positioning System
EL	External load
IL	Internal load
TD	Total Distance
HSR	High-Speed Running
RPE	Rating of Perceived Exertion
Effindex	Efficient Index
%HRmax	Percentage of Heart Rate Max
IR	Injury Risk
ML	Machine Learning
RA	Rolling Averages
EWMA	Exponentially Weighted Moving Average
SAID	Specific Adaptations to Imposed Demand
HIT	High Intensity Training
SSG	Small Sided Games
ISD	Inertial Sensor Device
T@VO ₂ max	Time at Maximal Oxygen Consumption Max
ASR/AP	Anaerobic Speed/Power Reserve
MD	Match Day
ACWR	Acute Chronic Workload Ratio
CV	Cross-Validation

ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
SHAP	SHapley Additive exPlanations
XGBoost	Extreme Gradient Boosting
KNN	K-Nearest Neighbors
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
TP	True Positive
FP	False Positive
TN	True Negative
FN	False Negative

List of table and figures

Table 1, Concept or construct definitions and explanations

Table 1.1, Relationship between Training Load, Performance, and Fitness Status on soccer training session

Table 1.2, Relationship between Training Load (external, internal and Total) and Fitness Status (calculated as external/internal load index) on soccer specific HIIT drill

Table 1.3, Relationship between Training (TL) and Match load (ML) considering external load volume (ELV) and external load intensity (ELI)

Table 1.4 Differences between external and internal indicators to assess soccer performance

Fig. 1 Soccer physical performance framework

Fig. 1.2 Soccer physical performance framework: a practical example

Fig. 1.2 Training load framework

Table 2. Main Soccer Internal and External intensity indicators

Table 2.1 Main Characteristics of studies that used internal/external load ratio or index

Table 2.2 Internal and external Device/parameters and Relationship/index External/internal load ratio of studies

Figure 2 – Intensity conceptual framework

Table 2.3, example of calculation of different training load on general aerobic running

Table 2.4, example of calculation of different training load on soccer specific aerobic task (i.e., Small Sided Games)

Fig. 2.1 Relationship between athlete fitness status, training load and injuries: a conceptual framework

Fig. 2.2 Conceptual framework: from training prescription to the informed-making process

Fig. 2.3 Report «soccer physical performance outcomes» related to match/training

Fig. 2.4 A framework on training/match load monitoring in soccer – how do practitioners assess training load? – a practical example on MD+4/-3

Fig.3 Prisma 2009 Fow Diagram

Table 3. Main Characteristics of the Studies included in the review

Table 3.1 Main Features of the Studies

Table 3.2 Machine Learning: Data Analysis Characteristics

Table 3.4 Machine Learning: Study Results Characteristics

Fig. 3.1 Funnel Plot Total Distance

Fig. 3.2 Funnel Plot Player Load

Table 3.4 EL indicators descriptions

Table 3.5. Predictive performance (weighted average of all the classes) of the machine learning algorithms and the baseline

Table 3.6 Matches' intensity profiles obtained by a data driven approach

Figure 3.3 Percentage of playing position in each players' matches' intensity profiles

Figure 3.4 Percentage difference of matches' intensity profiles occurrence between each SSG group and OM for each playing position

Figure 3.5 Percentage difference of matches' intensity profiles occurrence between each MBE group and OM for each playing position

Table 3.7 Overview of the difference in physical intensity between playing positions based on the different drills clustered (SSG and MBE)

Figure 3.6. Drills cluster framework based on the ML analysis

Fig. 3.7 Descriptions of the External Load indicators

Figure 3.8. Absolute value for each workload feature in each PCA component

Table 3.8. Descriptive statistics and statistical analysis of each score splitted by role and GD

Table 3.9 Descriptive statistics of the study parameters

Table 3.10 Performance evaluation of the LGBM model for predicting player profiles across all MD types

Figure 3.9 Performance of the LGBM model on validation data

Figure 3.10 Classification Report for Validation Data in the Developed Model (0 = MD, 1 = MD+2, 2 = MD+3, 3 = MD-1, 4 = MD-2, 5 = MD-3)

Figure 3.11 Confusion Matrix for MD types Prediction Using the LGBM Model on Validation Data (0 = MD, 1 = MD+2, 2 = MD+3, 3 = MD-1, 4 = MD-2, 5 = MD-3)

Table 3.11 Independent Testing for Model Performance Evaluation on Fresh Data

Figure 3.12 Contribution of parameters to LGBM Model Performance

Figure 3.13 Intensity profile across different match day (MD) types

Figure 3.14 Comparative MD types profile across all playing positions (a) distanceTotal/min; (c) distance >19.8Km/h/min; (d) Accelerations/min; (e) decelerations/min

Figure 3.15 Intensity profile across playing positions

Figure 3.16 Comparative Intensity profile across all playing positions

Table 3.12 Descriptive statistics.

Figure 3.17. Time series of TL, Recovery and Availability. The line reflects the team mean, while the shade is the team variability.

Figure 3.18. Autocorrelation plot of TL, Recovery and Availability. The bars reflect the autocorrelation coefficient of a specific lag, while the shadow shows the range of statistical significance.

Figure 3.19 Cross-correlation analysis of TL vs Recovery and TL vs Availability.

Figure 3.20 Cross Validation CV: Baseline ROC Curve (AUC = 0.56)

Figure 3.21 Cross Validation CV: ROC Curve with ACWR Features (AUC = 0.57)

Figure 3.22 Cross Validation CV: ROC Curve with EL/IL Features (AUC = 0.59)

Figure 3.23 Cross Validation CV: ROC Curve with ACWR + EL/IL Features (AUC = 0.62)

Figure 3.24 Train/Test Split (Temporally Constrained): Train/Test Split ROC Curve (AUC = 0.59)

Figure 3.25 Alternative Model A ROC Curve (AUC = 0.81)

Figure 3.26 Alternative Model B ROC Curve (AUC = 0.77)

Figure 3.27 Feature Importance Analysis

Figure 3.28 SHAP Probability Analysis

Figure 3.29 Cognitive bias on training load injury causation: a conceptual framework

Figure 3.30 Non-contact injury risk prevention strategies: a conceptual framework

Figure 3.31 Strong vs weak athlete and non-contact injury risk: a conceptual framework

Figure 3.32 Evidence-based training prescription: a conceptual framework

Figure 3.33 Decision-making based on a data-informed approach: a conceptual framework

Figure 3.34 Data-informed approach to training prescription: a conceptual framework

Table 3.13, Relationship between High-Speed running/Peak Speed, and Injury Risk considering the differences between strong and weak players: an example from the microcycle

Table 3.14, A data-informed approach based on the external load data (sprinting) collected in the microcycle considering playing position

Chapter I – Introduction

1.0 Overview

Training load monitoring represent a “on-field” common practice to optimize soccer training prescription aiming to enhance physical performance trying to reduce the injury risk (1-6). Understanding both external load, considered as the physical work prescribed in the training plan (e.g., measures of total distance covered (or in specific speed bands), accelerations, or metabolic power and internal load (i.e., the athlete’s physiological response to a given external load performed), offer a necessary practitioners’ support in informed-making concerning the training prescription (6). Indeed, training process aiming to prepare players to withstand the match-demand, accordingly, practitioners can tailor training to enhance the physical performance seeking to reduce injury risk starting from the knowledge of the match-demand (derived from external load/GPS data) and physiological demand. Worth noting, in order to prescribe optimal training (i.e., balancing the training dose and recovery,) to reach the desired adaptation, whole components of soccer performance must be considered such as training and recovery aspects, the athlete’s fitness status (i.e., physiological assessment), keeping into account the training methodologies principles as well as the match-day target derived from microcycle schedule (7-9).

Several studies have been published on training load monitoring, physical performance and injury risk reduction in soccer. The “era” of Big Data arises from an exponential technologies development to monitor both training and competition as well as physiological aspect of performance (10). This period is strongly characterized by the need to analyse a huge amount of data daily collected through such devices as GPS and IMU. To address this complex analysis, has been established that traditional statistic methods lacking to this propose. Indeed, the role of artificial intelligence and its daily application is spreading widely in many areas of the development sector such as finance, business and sports science. In the latter field, Machine learning (ML) is a branch of AI and computer science that focuses on the using data and algorithms to enable AI to imitate the way that humans learn, gradually improving its accuracy. Machine learning uses algorithms trained on data sets to create models that enable machines to perform tasks that would otherwise only be possible for humans, such as categorizing images, analyzing data, or predicting price fluctuations (11-13). In this context, especially in soccer, ML has been increasingly employed aiming to predict injury as well as to understand specific performance aspects. Despite several studies has been published (12, 14-16), literature lacks to provide an evidence-based consensus to apply the best strategies to optimize soccer training and competition monitoring aiming to enhance physical performance while attempting to reduce injury risk.

Relevant aspects such as the relationship between training load monitoring and training outcomes such as physical performance, recovery ability, training prescription and injury risk reduction should be yet better established and clarified aiming to provide an evidence-based consensus about strategies in a real word scenario as well as theoretical and methodological aspects in scientific community. Specifically, the difference between training drills and official match as well as an in-depth understanding of the external load profile of the playing position during different soccer activities and tasks, has not yet been provided through the machine learning approach.

The complex relationship between training load, physical performance and injury risk reduction has never been clearly established despite studies have attempted to this propose. Specifically, Studies fail to provide scientific evidence for decision-making based on a data-informed approach, leading to a gap in the literature on training monitoring and training prescription. Furthermore, the scientific community is far from providing a contribution on injury prediction in a real scenario and in providing complete and unanimous injury prevention strategies. This could be due to high variability among studies methodologies as well as the atherogenicity in different contexts. The effective application of ML models for sports injury risk prediction is hampered by widespread variability in study design, methodological approach and statistical analysis. Instances in which ML models have failed to outperform traditional approaches to sports injury risk prediction demonstrate the need for more granular and integrated datasets. These datasets may be capable of supplying the volume, variety and quality of data required for the effective application of ML approaches.

With this in mind, preliminary studies suggest implementing some strategies to optimize training prescription aiming to enhance physical performance while reducing injury risk considering the implication of machine learning approach. In the third chapter we will delve into the application of Machine Learning in soccer showing how practitioners can apply ML to understand the relationship between training load, playing position in different drills typologies as well as the complex relation between training load and recovery.

The current state of research on training load, machine learning, and injuries in sports science reveals several notable gaps. One critical issue is the lack of standardization in the metrics used to measure training load. Studies frequently employ a wide range of external (e.g., distance, accelerations) and internal (e.g., HR, RPE) load indicators, making it difficult to compare findings and establish generalizable conclusions. This inconsistency complicates the development of clear guidelines for practitioners.

Machine learning, while promising, remains limitations in this field. Many studies still rely on traditional statistical methods that fail to capture the complex, non-linear relationships inherent in training load, recovery, and injury risk. Even when ML is applied, small sample sizes are a common

limitation, reducing the generalizability of findings and increasing the risk of overfitting, which can compromise the reliability of these models in practical settings. Additionally, many ML models lack external validation, raising concerns about their applicability across different teams, populations, and contexts.

A further limitation is the lack of transparency in the methodologies employed. Key details such as data preprocessing, hyperparameter tuning, and feature selection are often omitted, hindering reproducibility and the critical assessment of results. Another challenge lies in the narrow scope of many studies, which often focus on a limited set of variables. For example, Injury is a multifactorial phenomenon influenced not only by training load but also by recovery, psychological factors, and biomechanics as well as individual characteristic, player's previous injuries. However, the broader context is frequently overlooked, which limits the predictive accuracy of injury models.

The interaction between training load and recovery is particularly underexplored, despite its importance in understanding performance and injury risk. Few studies adequately examine how recovery metrics, such as Total Quality Recovery scale, mediate the effects of training load. Similarly, positional and contextual factors—such as match intensity, environmental conditions, and specific playing position—are rarely considered, despite their significant influence on individualized training load and injury risk.

While ML offers theoretical potential for real-time monitoring and prediction, its practical implementation remains limited. Computational challenges, data collection reliability, and usability issues need to be addressed to make these systems more accessible and effective in real-world scenarios.

In summary, advancing this field requires addressing these gaps through multidisciplinary collaboration, rigorous study designs, larger datasets, and greater transparency. Efforts to validate ML models externally, standardize metrics, and integrate recovery and contextual factors will be crucial for translating research into actionable insights that enhance performance and mitigate injury risks.

In the next paragraphs we will provide a theoretical overview on ML methods focusing on injury forecasting as well as an overview on training load, soccer demand, performance analysis will be reported.

This thesis will attempt to provide a theoretical and practical contribution based on the gaps identified in the literature. Accordingly, the main research will answer relevant research questions as follow:

- 1) How practitioners can assess training load (including both intensity and volume) considering the differences between training and competition for each playing position aiming to support the training prescription process?

- a. How practitioners assess physical performance?
 - b. What is the external load difference between official match and different training drills among playing position?
 - c. What is the current understanding of training intensity in soccer performance monitoring?
 - d. How practitioners translate the information derived from training load monitoring to training prescription?
- 2) How can machine learning be implemented to understand the relationship between training and competition considering playing position to enhance physical performance and reduce injury risk?
- a. What is the relationship between training load and training outcomes?
 - b. Can external and internal load be highly correlated?"
 - c. Is machine learning implicated in understanding training load, physical performance, and training outcomes?
 - d. How does machine learning allow to profiling playing position considering different drills typologies?
 - e. How do practitioners assess the weekly training load?
 - f. Is there an association between training load and recovery?
 - g. It is possible to predict injury thought machine learning approach?
 - h. Can the practical application of the data-informed approach reduce the risk of injuries?

1.1 Aims and Objectives of the thesis

The overall aim of this thesis was to further the current understanding around the training load monitoring, physical performance and training prescription, focusing on the implication of machine learning on training load, physical performance analysis, and injury risk in soccer players. With this proposes, we tried to deeply understand the complex relationship between training load and training outcomes such as physical performance and injury risk.

We addressed over the course of three experimental chapters, which set out to achieve the following objectives:

1. Provide a summary on training load, performance analysis, reduction of injury risk, match-based demand and physiological-based demand on soccer, and machine learning. (*Chapters 1*)
2. Offer an overview on intensity concept in soccer through a conceptual framework (*Chapters 2*)
3. Provide an overview with practical proposal on training prescription based on players monitoring in a real word soccer scenario (*Chapters 2*)
4. To investigate the relationship between external load and internal load indicators and injury using machine learning in professional soccer thought a systematic review. (*Chapter 3*)
5. To investigated the association between match-related physical activity profiles and playing positions in different tasks through a data driven approach and machine learning (*Chapters 3*)
6. To analyse the intensity profiles and key indicators in standard microcycles of professional soccer players through a machine learning approach (*Chapters 3*)
7. To evaluate the weekly training load through a new training load and performance score on professional soccer players based on a machine learning approach (*Chapters 3*)
8. To explore the association between internal load responses and recovery ability in young professional soccer players through a machine learning approach (*Chapters 3*)
9. To predict injuries through a machine learning approach (*Chapters 3*)
10. To provide a conceptual framework on Hamstring Injuries in Soccer focusing on the practical insight on Data-Informed approach (*Chapters 3*)

Chapter I will provide an overview on soccer demands, training load, injury, performance analysis, and machine learning. To address this, a narrative review with conceptual framework related to Physical Performance and Training in Soccer will be reported.

Chapter III will offer an overview on intensity concept in soccer reporting a conceptual framework. Moreover, we will also provide an overview in which both theoretical aspects and practical proposals on training prescription based on player monitoring in a real soccer scenario will be presented by addressing a review with conceptual framework.

Chapter III will focus on a deeply investigation on training load considering playing position and different drills. Specifically, we apply a machine learning approach to profiling the playing position during different drills including official match from external load data. Indeed, ML allows to define the intensity of a soccer exercise by indicating whether a stimulus is predominantly neuromuscular

or metabolic also by playing position offering valuable insight for practitioners during the training prescription process. We will also provide the application of new load and performance score to investigate the microcycle training load through a machine learning approach. Indeed, the use of a summary indicator can help to obtain an overview of both the total load and the intensity in order to easily compare both players and training sessions. To deeply understand the intensity profiles and key indicators in standard microcycles of professional soccer players, considering the differences between playing position we implemented a machine learning approach.

Moreover, we will investigate the relationship between training load and recovery through a machine learning approach.

At the end of this section, we will report a review with conceptual framework on non-contact injury prevention strategies applying the data informed approach aiming to understand if the exclusive implementation of “data” can be appropriate to this propose.

In conclusion, the studies shown in this thesis provided promising results highlighting auspicious and useful insight when machine learning is implemented to investigate the complex relationship between training load and training outcomes such as physical performance analysis, recovery, and injury. However, limitations concerning the application of machine learning approach in real context will be also provided.

List of publications/projects discussed within Chapter I:

Guglielmo Pillitteri, Filipe Manuel Clemente, Marco Beato, Alessio Rossi, Hugo Sarmiento, Antonio Palma, Antonino Bianco, Giuseppe Battaglia - An Updated Conceptual Framework on Physical Performance and Training in Soccer. A narrative review - Strength and Conditioning Journal -

1.2 An Updated Conceptual Framework on Physical Performance and Training in Soccer. A

narrative review - Guglielmo Pillitteri, Filipe Manuel Clemente, Marco Beato, Alessio Rossi, Hugo Sarmiento, Antonio Palma, Antonino Bianco, Giuseppe Battaglia – Strength and Conditioning Journal

1. INTRODUCTION

Soccer performance is defined as the set of multiple, complex, and interdependent factors, such as physiological, psychological, technical, and tactical, including individual and contextual factors that should be considered during training practice (17). In the last 20 years there has been a considerable scientific interest in soccer training regarding the close relationship between physical performance, training load (TL), and injury monitoring (18-23). The training process is the systematic repetition of physical exercise that results from the interaction of multiple factors such as physiological, biochemical, anatomical, and physical changes (i.e., performance outcomes) (24, 25).

Given the multifactorial component involved into the training process, sport science departments working in soccer aims to design training programs and implement monitoring strategies to obtain the wishes players' adaptations. Indeed, monitoring TL (which is categorised as internal load [IL] and external loads [EL]) and recovery status can contribute to assessing an athlete's adaptation and ensure an adequate recovery-stress balance to improve performance and reduce the risk of injury (26, 27). However, previous research reported about new constructs such as wellness and performance readiness, although these have never been fully clarified or validated (17, 28). The fitness-fatigue model (i.e., the Banister model) explained the relationship between TL, positive adaptations (fitness), and negative adaptations (fatigue) (29). However, this dose-response relationship depends on different determinants of players' physical fitness levels (i.e., fitness status), since the same stimuli could be perceived differently by athletes (30). For example, the same EL could lead to higher or lower internal responses among athletes (30, 31). Recently, some conceptual frameworks related to physical training have been developed (2, 17, 30, 32). Despite the improvement provided by the interesting frameworks that provided a useful understanding of training load and physical performance, there may still be misconceptions, misinterpretations, and possibly inappropriate and inaccurate conceptualizations among practitioners in the context of soccer training physical performance. Indeed, some issues need to be clarified and well defined (for example, the relationship between physical performance, TL, and fitness status,). Furthermore, we noticed inconsistent terminology when both researchers and practitioners refer to physical performance in soccer. In fact, a distinction between performance and physical performance is consistently missing among studies as well as a difference is missing between physical performance related to external load factors (match-demand performance) or related to physiological factors (physiological-demand performance). Worth noting, we noted a lack of uniformity in training load calculations across studies. Indeed, for an appropriate calculation and determination of the training load, every external or internal load factor (indicator) should take into account the time factor, e.g., duration of the training or

competition (4, 17, 28, 32). Conversely, others, such as well-being and readiness measures, should be validated to help coaches better apply these concepts in training practice. For such a reason, a new framework embedding TL monitoring, wellness and performance readiness is needed to support practitioners in programming soccer training and evaluate its effects (2, 8, 33).

Hence, the aim of this narrative review was (1) to report definitions related to training effects, physical performance, training load, fitness status, and fatigue-recovery process considering the validity of the common measures used in soccer; (2) to revise conceptualizations aimed to describe and clarify physical performance, load monitoring, athlete's fitness status, and fatigue in soccer highlighting the differences between them by providing simple calculation examples; (3) to design a new conceptual framework on physical performance and training in soccer; (4) finally, to report practical examples of the relationship between physical performance, training load, and fitness status to improve the monitoring of decision-making processes and training prescription.

2. BACKGROUND OF CONCEPTUAL FRAMEWORKS

A conceptual framework “synthesizes evidence, aids in understanding the phenomena under investigation, informs future research, and serves as a guide in practical settings” including explanations of the relationships of the construct to be measured (34). This explanation is consistent with a generic definition that describes the structure that researchers believe best explains the phenomena to be investigated (17, 35). It can be done through visual representation and logical structure, illustrating supposed relationships between key concepts, constructs, or measures (e.g., EL and IL indicators).

Qualitative research includes a conceptual framework that allows for an understanding of theoretical phenomena, such as physical training that translates into a practical setting. Although several studies in soccer have provided practical solutions such as the use of simple scale (36), field and laboratory tests (37), and implementing a range of TL devices (related to both internal and external) (21, 22, 38, 39), conceptualizations regarding physical performance, TL, athlete's fitness status, and performance readiness are still lacking.

The development of our conceptual framework includes an integrative synthesis of the literature and analysis of existing frameworks linked to information and concepts from previously established

models and theories. The conceptualizations process (i.e., the process in which imprecise constructs and their constituent components are defined in precise terms) was used in this qualitative study (17, 40). To understand the interactions between TL and training response, the main framework and conceptualizations initially included in this study started with the Banister fitness-fatigue model (29). Another framework included in this paper was carried out by Impellizzeri et al. (30) in which authors provided an outstanding contribution to clarifying TL concepts. Gabbett et al. (2) reported an interesting practical guide to the strategic planning, analysis, interpretation, and application of athlete monitoring data in the sports environment. Recently, Jeffries et al. (17) have examined a revised conceptual framework on the physical training process providing research and practice-related implications. Finally, Beato et al., has recently suggested a new framework for the monitoring of readiness to train and perform in soccer (41).

2.1. Frameworks on Physical Training, Training Load, and Athlete Monitoring Process

In this section, the above frameworks were summarized to further revise the concepts related to the relationship between physical performance, TL, fitness status, recovery, and readiness in soccer. To fulfil this proposal, definitions of concepts or constructs (Table 1) and practical calculations as examples (Table 1.1-1.4) have been included.

The first attempt to implement a generic conceptualization framework of physical training was made by Impellizzeri and colleagues (24, 30). The authors proposed, defined, and conceptualized the essential measurable components of the training process and its outcomes in the context of physiological assessment in soccer (24). The central concept of this physical training framework was the prescription of appropriate exercises according to the training target and the periodization that will determine the psychophysiological responses (stimuli) and consequently the athlete's adaptations (i.e., training results) (24). In this way, the concept of TL was clarified and refined through the theoretical framework, including definitions of both IL and EL to avoid misapplications or misinterpretations of these originally proposed concepts (30). Indeed, the concept of IL-EL was not originally operationally conceptualized so the authors suggested integrating both EL and IL measures for training monitoring (30).

Jeffries et al. (17) integrated the previous framework by Impellizzeri and colleagues (30) with the Banister fitness-fatigue model (29) and the Performance Potential Metamodel (PerPot) (42) including

measurable components and concepts. Indeed, the Banister model described performance (output) as a quantifiable outcome of two key training responses (i.e., fitness and fatigue) derived from the applications of the training impulse (input). At the same time, the PerPot Metamodel used a different computational approach to simulate the relationship between load and performance (42). However, Jeffries et al. (2021) (17) reported inappropriate use of the terms fitness and fatigue and replaced them with positive and negative training effects. Moreover, the authors expanded the framework with a training effect construct, including acute and chronic dimensions. The final version of the theoretical framework reported the following four constructs: (1) training effects; (2) training effect measures; (3) sports performance outcomes; and (4) individual and contextual factors. Furthermore, the authors provided a label with conceptual definitions and operational definitions (17). Four conditions have been reported regarding the training effect (i.e., acute, chronic, positive, and negative). Interestingly, the authors stated that both positive and negative effects could occur at the same time (for example, a positive impact such as increased muscle protein synthesis after strength training may be associated with a negative effect related to neuromuscular fatigue (43)), which would lead to a temporary decrement in readiness, but later on, leading to an improvement (i.e., adaptations due to the supercompensation process) in sports performance outcome (41). Indeed, sport performance outcomes result from balancing positive and negative training effects. Based on this framework, performance outcomes can be predicted using computational methods that consider external training load measures as “proxies” (surrogates) to quantify the negative and positive effects. Accordingly, the balance between these two effects (positive and negative) determines the performance outcomes. This is supported by the close causal relationship between TL and training effects (21). In this way, the framework reported measures of training effects that were classified as performance, physiological, subjective, and other measures (cognitive, biomechanical, etc.).

Given the relationship between training load on performance and injury, Gabbett et al. (2) provided the “athlete monitoring cycle strategy” for interpreting athlete monitoring data. The “cycle” describes: (1) the EL performed by athletes; (2) the athlete’s response to the training load (i.e., IL); (3) whether the athlete is tolerating the training load (i.e., perceptual well-being or other readiness measures); and (4) whether the athlete is physically and/or mentally prepared to be subjected to another physical stimulus (i.e., readiness to train/compete). The authors produced a matrix at each step of the cycle to support practitioner decision-making. Coaches can modify the TL of the next session (i.e., increase, maintain, or decrease workload), trying to understand if an athlete is ready to train or needs extra recovery. In this way, practitioners can provide an adequate balance between the

workload and recovery to elicit supercompensation process to optimize the training effect (i.e., enhance physical performance) while reducing injury risk.

In order to enhance physical performance while reduce injury risk, given the high training and matches physical-demand, understanding whether players are prepared (psychologically and physically) to compete safely (i.e., in a state of physical and mental health), the monitoring of players' readiness represent a paramount strategy for practitioners. Indeed, Beato et al., (41) have reported a conceptual framework on readiness suggesting that practitioners should include both objective (e.g., countermovement jump and heart rate [HR]) and subjective measures (athlete-reported outcome measure [AROM] instruments) in their monitoring practices aiming to identify patterns or “alert” related to player’s health condition and make informed decision concerning training and/ or match availability (41) (i.e., can a player be subjected to certain physical loads based on his state of readiness?).

In the next section of this work, the concept of “soccer physical performance” is introduced conceptualized from Jeffries et al. (17). The differences between training/match load, physical performance, and fitness status are highlighted and practical examples are presented relating to the essential and indivisible relationship between EL and IL (30). Finally, the concepts relating to the framework carried out by Gabbett et al. (2) are reviewed with providing practical examples.

3. DEFINITION OF SOCCER PHYSICAL PERFORMANCE

Table 1 reports the most relevant concepts or constructs considered in our framework. Definitions and explanations (e.g., what they measure and how these factors can be measured) have been included to provide a useful guide to better understand our framework. In sport, performance can be defined as “the accomplishment of goals by meeting or exceeding predefined standards” (44). The concept describes individual or collective behaviour patterns according to skills, abilities, and specific performance conditions. In soccer, match performance can be described as the interaction of different technical, tactical, physical and mental factors (45, 46). Although these performance aspects are closely related in a practical context, in this narrative review the physical performance element of soccer is the focus. This multidimensional concept of physical performance is reciprocally related to both physical and psychological factors. It is worth noting that soccer match physical performance can also be influenced by tactical requirements and playing positions (47-51) as well as can be strongly influenced by cognitive factors such as mental fatigue (52).

Several studies have investigated the factors involved in physical performance demands of a soccer match to appropriately prescribe training (8, 24, 53-55). Soccer is a high-intensity intermittent sport that includes, rapid changes of directions, accelerations, decelerations, jumps, and technical actions (21, 56, 57). In addition, high-speed activities have been considered a crucial physical component in soccer, where professional players regularly cover total distances ranging between 10-13 km of which around 900 m and 250-300 m travelled at high-speed running (HSR; speed ranging from 19.8 km*h⁻¹ to 25.2 km*h⁻¹) and sprinting (speed $\geq$ 25.2 km*h⁻¹), respectively (37, 58, 59). Indeed, previous studies have reported that sprinting bouts generally occur every 90 s and each of these sprints lasts approximately 2-4 s during a match, resulting in 1,000-1,400 high-intensity, short-duration activities (60, 61). Readers can find more complete details on physical performance demands by referring to reviews carried out by Harper et al. (62), Mackenzie & Cushion (63), Rico-González et al. (64), Sarmiento et al. (65), and Delves et al. (66, 67).

Previous studies have provided detailed information on the physiological aspects required by competition (8, 24, 33, 46, 49, 55, 60, 61, 68-70). In particular, Stolen et al. (61) reported that the energy demand in soccer players mainly depends on aerobic capacity even if the anaerobic components contribute to performance (8). Indeed, studies reported higher levels of aerobic capacity improve recovery from high-intensity interval loads (i.e., anaerobic actions) (24, 46, 71). In contrast, a recent review revealed that the relationships between repeated sprint capacity and aerobic capacity were low to moderate, leading to the need for further investigation to understand the physiological interactions and energy metabolism to determine the best sprint and aerobic capacity (72). However, aerobic capacity also seems to be a prerequisite for improving the efficiency of anaerobic capacity when performing high-intensity intermittent efforts (8, 46, 56) despite conducting intensified training (e.g., high intensity interval training – speed endurance training) periods to enhance physical performance in elite football players is required (73).

As both the physiological and match-demand components are involved in soccer performance, three components of soccer physical performance have been conceptualized in our framework: (1) the first is related to match-demand (i.e., an external component such as distance, speed, accelerations, metabolic power, change of directions, and strength); (2) the second concerns physiological-demand (internal component such as HR, maximal oxygen consumption, rating of perceived exertion); (3) the third concerns athlete-related performance and it refers to an individual internal response to a given EL. Our framework will be detailed in the section 3.2. In the next section we will address the performance definition and delve into the physical performance assessment overview

in soccer. These aspects are crucial to strength the concept about the need to consider several indicators to assess the multifactorial aspects of physical performance in soccer.

3.1. Performance Assessment in Soccer through Physical Performance Indicators

Performance has been defined as “the accomplishment of goals by meeting or exceeding predefined standards” (44). Accordingly, as reported in Figure 2, it should be necessary to identify a gold standard of reference to translate the "predefined standards" into numerical and objective measures allowing an evaluation of performance by carrying out a comparison. Indeed, assessing physical performance involves comparing “what an athlete did” with reference values (i.e., physical match demands and physiological requirements) of the same players, team, or reference teams. However, we highlight that physical demand is related to several factors such as individual (i.e., genetics, psychological characteristics, training background, fatigue conditions), and contextual factors (i.e., such as environmental, social and cultural factors) (17). It is worth noting that previous work has shown between-player, between-position, between-match, and within-player variability when considering match physical performance metrics (especially for HSR), which must be considered when evaluating the practical significance of between-match (or players) changes (48, 74, 75).

Given the complexity of soccer physical demands, several indicators should be considered by practitioners to fully understand the effects of training or match (76, 77), as there is no single reference for the outcome of soccer physical performance (17, 30). Indeed, it would be impossible to consider a single indicator (derived from both EL or IL metrics) to describe physical performance considering both the match-demand (e.g., speed, accelerations, and metabolic power parameters) and the physiological component (e.g., the aerobic and anaerobic systems). Several studies have dealt with physical performance assessment by considering training load indicators. For example, Miguel et al. (38) carried out a review on load measures in training/match monitoring in soccer, while Oliveira et al. (78) reported detailed reference values for external and internal training intensity monitoring in young male soccer players. Studies have also investigated soccer physical performance by measuring physiological indicators (46, 55, 60, 61). For example, Helgerud et al. (46) considered HR, lactate (LA), and maximal oxygen consumption (VO_{2max}) as physical performance indicators. However, given the contribution provided by our framework, where both the match-demand model and the physiological-demand model have been considered, it seems that in soccer it is impossible to refer to an absolute and general concept of physical performance as there would be the risk of losing important

and fundamental components. Accordingly, we will detailed our framework in the next section describing each component of physical performance we have conceptualized (i.e. match-demands performance, (2) physiological-demand performance, and (3) athlete-related performance).

3.2. Conceptual Framework of Soccer Physical Performance: Differences Between Match-Demands Performance, Physiological-Demand Performance, and Athlete-Related Performance (Fitness Status)

Considering previous frameworks on physical training, we have revised some concepts focused on “soccer physical performance.” A new framework presenting the conceptual difference between (1) match-demands performance, (2) physiological-demand performance, and (3) athlete-related performance, has been reported in Figure 1, which provides an essential explanation for soccer physical performance.

Match-demand and physiological-demand performance can be seen as different but complementary and essential components of soccer physical performance. Match-demand performance is based on results of competition-demands (i.e., technical tactical and physical factors) by answering the question “What did the athlete do in the match or competition compared to the reference values?” In this case the “performance measure” cannot disregard the concept of “comparison.” Each value obtained should be compared with a reference value. In detail, the meaning of performance can be obtained through a longitudinal assessment, a transversal assessment, and the external activity of the match-demand (i.e., gold standard). Indeed, the values obtained from match-demand through various external load indicators (e.g., total distance or total distance/min) should be considered as references values to compare each training with official match. This approach allows to understand if a player is ready to withstand the demands of the game and to evaluate the training objective. In fact, according to the microcycle training program, a certain training section such as the game day (MD-3) should focus on high-speed running and sprinting to adapt the players to better performance while protecting the hamstrings from injuries during official competitions (7, 67, 79-81). For example, in figure 1.1, Training 2, athlete A performed the same HSR as match-demand references values; athlete A performed a greater HSR than their previous activity (i.e., longitudinal

assessment); athlete A performed the same HSR e than athlete B and less than athlete C (i.e., transversal assessment) (Figure 2).

Physiological demand performance refers to athlete responses (i.e., internal components) during matches or competitions. Figure 1.1 also relates the athlete's internal responses to a given external activity performed to understand the athlete-related performance. For example, it could happen that athlete A and athlete B performed the same HSR resulting in different average HR or rating of perceived exertion (RPE) (82). In this case, it is simple to calculate (through an external internal load ratio) (83) that the athlete with a higher average HR or RPE has a lower fitness status (30, 83) or may be in a condition of fatigue (49, 84, 85) and low recovery. However, other contextual and individual factors can explain the complex relationship between EL and IL (18, 20, 21, 31, 57, 83, 85). In this scenario, athlete-related performance could be considered as the athlete's fitness status rather than "performance" referred to as "how much 'physical work' an athlete performed compared to a previous reference (i.e., match-demand or physiological demand)." It is worth noting that, to operationalize physical performance concepts (i.e., match demands, physiological-demand, athlete-related), we have used the same "intensity" indicators as both external (e.g., HSR, metabolic power, accelerations, distance per minute) and internal (e.g., HR, RPE) considered to calculate TL (external and internal). However, "performance" and "load" explain two different concepts despite being closely related. Indeed, the absolute load (e.g., TD or HSR distance) registered during a match is strictly related to the time duration. In fact, it would be possible to compare the absolute external load of two players only if both had played the same amount of playing time. While the concept of physical performance is related to the "intensity" (e.g., distance per minute or HSR per minute) performed considering playing time. In this way, it is possible to compare the physical performance of two players even if they have played different playing time. These concepts are further explained in the next sections (Table 1.1 and Table 1.2) by providing simple calculations to understand the relationship between TL and physical performance. In the next section will be report an overview about the main performance indexes and scores have been published in literature. This supports one of the key components of our framework in terms of physical performance (i.e., athlete-related performance).

3.3. Performance Index and Score

Several studies carried out in soccer have investigated EL and IL integrated approaches to investigate the athlete's response to a given external load stimulus. In particular, literature shows various integrated approaches implemented to create a new index or ratio for IL and EL. In detail, Grünbichler et al. (86) set a training load (e.g., Effindex), calculated as the ratio between equivalent

distance (distance that a player would have covered theoretically at a steady pace) and TRIMPmod (modified training impulse that describes time spent in certain HR zones multiplied by a weighting factor). This index was influenced by total distance and sprinting distance. A contribution has been offered by Pillitteri et al, who computed two Scores (i.e., Load and Performance), starting from several external and internal load indicators, through a machine learning approach (87).

In our framework, the external/internal load ratio explains the athlete-related performance (fitness status) since for the same EL carried out, the athlete with a lower internal response, usually shows a better level of fitness (Figure 1). Worth noting, the athletes' fitness status can be assessed through several both physiological and performance test (on field and laboratory). However, these methods require high time-cost as well as specific equipment. Consequently, the evaluation of the physical fitness status of athletes in the daily routine through tests would not be very applicable in the real context, therefore the use of simple indices seems the most effective and functional way. To deeply delve into the knowledge about aforementioned indexes, we refer the reader to the literature review carried out by Pillitteri et. al. (14, 87).

4. A REVISED CONCEPTUAL FRAMEWORK OF TRAINING LOAD IN SOCCER

The IL and EL constructs have been presented in a previous study by Impellizzeri and colleagues (2019) (30). Our review considered this framework and argued the two related constructs on the EL. The two concepts refer to “volume” and “intensity” which are combined with EL (related to match-demand) resulting in two constructs as follows: external load volume (ELV), and external load intensity (ELI) (Figure 1.3). To compute both ELV and ELI, we have multiplied the values derived from given indicators and time (duration) as suggested by Coyne et al., (88). In detail., volume refers to the total amount of work carried out in a given period (e.g., the total number of intense accelerations or sprints performed in 90 minutes), while the amount of work carried out in the unit of time (e.g., distance per minutes or number of intense accelerations per minutes) can be considered as measures of “intensity”. Both volume and intensity indicators should be considered when comparing the match load with the TL. Considering only the volume indicators we would have a partial overview of the load carried out as reported by Pillitteri and colleagues (32). Furthermore, the volume parameters do not explain the concept of intensity related to physical performance. These have been clarified by providing simple calculations through practical examples, as shown in Tables 1.1-1.4.

Integrating IL and EL measures for monitoring training or match have been considered as conceptually advantageous (4, 14, 32, 89). For example, it can be used to understand how an athlete is coping his training program (2). Athletes who show a lower IL than standardized EL, completed under similar conditions, are assumed to reflect a higher fitness status, despite different factors could determine the athlete's internal responses (e.g., sleep, fatigue, mental stress). As discussed in the previous section, using the external/internal load ratio (90) is a simple and effective way that provides useful information on the player's fitness status in a daily routine monitoring.

5. DEFINITION OF SOCCER PLAYER'S FITNESS STATUS

From a general perspective, fitness status has been defined as “a set of attributes that people have or achieve that relates to the ability to perform physical activity” (91). Fitness has also been operationalized as “a set of measurable health and skill-related attributes” including cardio-respiratory fitness, muscular strength and endurance, body composition, flexibility, balance, agility, reaction time, and power (92). Therefore, the athlete's fitness status is related to the positive influence of long-term training (i.e., adaptation), while acute fatigue describes the negative response to recent training stimuli. Indeed, to support the match and/or training demands, high physical fitness levels are needed to cope with the increasing number of matches during a season and possibly reduce the injury risk (27, 84, 93). In this context, several measurable components contribute to detecting physical fitness. The main components were divided into two groups: one related to health (i.e., cardiorespiratory endurance, muscular endurance, muscular strength, body composition, and flexibility) and the other related to athletic ability (91, 94). In the next section we will reports the main strategies to assess athletes' fitness status offered by literature.

5.1. Fitness Measures and Player's Fitness Assessment in Soccer

A physical fitness assessment includes several measures of body composition, cardiorespiratory endurance, muscular fitness, and musculoskeletal flexibility through field and laboratory tests. Jeffries et al. (2021) (17) reported the primary measures of “performance” (related to fitness component as strength or endurance) and “physiological” (suitable measures for monitoring acute or chronic training effects). For example, the countermovement jump test can be performed to assess both neuromuscular fatigue (after the training session) and the chronic training effect on lower body ballistic force production (proxy measure) or jumping performance. While physiological measures

include VO_{2max} , running economy, lactate threshold, and creatine kinase. Along with these measures, subjective evaluation scales have been widely used in recent years, even if not all of them are adequately validated. For example, wellness items (e.g., Hooper Index (95)) are implemented to measure fatigue, sleep quality, stress, and muscle soreness (96). At the same time, others have been used to investigate training pleasure and satisfaction (97, 98). Moreover, recovery status has been studied by applying subjective scales such as the Total Quality Recovery (TQR) scale (98). However, it is not clear whether these can be used to measure acute effects or chronic or individual and contextual factors (17). It is worth noting that Gabbett et al. (2017) suggested monitoring perceptual well-being to understand if the athlete is tolerating the workload (2). In this regard, there is a high correlation between fitness levels and the ability to recover from workloads, so players with higher fitness levels will recover faster and with better quality from previous training or match load (26, 93, 98, 99). As previously reported, in the soccer context, the most direct and practical way to understand the athlete's fitness status (i.e., “how the athlete responds to the load”) concerns the application of the external/internal load ratio (Figure 1). Tables 1.1, 1.2 show some practical examples.

5.2. Relationship Between Wellness and Training Load in Soccer: is an athlete ready to train or compete?

Given the high level of stress players are subjected to due to the demands of training and matches, the need to be able to stay prepared (psychologically and physically) throughout the season is essential to perform at highest level. Accordingly, the monitoring of player's readiness (i.e., the state of being fully prepared to train and perform physically and mentally) represents an important strategy for practitioners (41). Since readiness includes both fatigue and health monitoring, wellness has been included in the readiness construct (41). Readiness monitoring tools include both objective (quantified often via the use of technology) and subjective (those that are self-reported given an individual's internal feelings and perceptions). Objective measures include neuromuscular fatigue assessment such as countermovement jump test, broad jump, sprint test, a submaximal fitness test, strength test, peak power cycle ergometer test and other measures (saliva and blood test). In the other hand, subjective perceptual scales (subjective athlete-reported outcome measure [AROM]) play an important role in monitoring and optimizing player performance used to assess players' readiness, specifically acute (positive or negative) training effects (e.g., fatigue status after a match or a period of training). In particular, several psychometric indicators have been implemented to investigate the relationship between the subjective states of well-being, recovery, and mood with physical, technical,

tactical, and psychological outcomes in elite soccer athletes (50, 100). Indeed, the physical, technical, tactical, and psychological components of a player at a given training stimulus can be affected by an increase in fatigue due to a high TL, an imbalance between the training-recovery process, and the player's fitness status (101). Consequently, increased pre-fatigue states and poor recovery during training can lead to decreased physical performance, inducing negative psychological outcomes during training sessions and competitions (98). Several studies have found that HI sub-scores (i.e., sleep quality, overall stress, fatigue, DOMS) and TQR score can predict soccer performance, highlighting that high HI and TQR scores are significantly associated with heavy TL (98). In contrast, Duignan et al. (2020) showed that in a real-world scenario, these measures are unlikely to be influenced by TL in isolation, as they will also be determined by recovery, psychological and social influences (the directions of the relationship were predominantly negative when TL increased, wellness decreased). This suggests that these measures may explain the players' "readiness" than a linear training "response." Indeed, authors found mainly trivial results evaluating the effect of pre-training wellness on subsequent training output (102). As a result, several scientific research have studied this complex relationship between well-being markers and TL. For example, Moalla et al. (2016) studied the relationship between daily TL and HI, showing a significant relationship between TL and perceived sleep stress, fatigue, and DOMS. This finding indicated that TL affects the well-being status of professional soccer players (103). In the same way, Pillitteri et al., (104) thought a time series analysis (i.e., autocorrelation analysis, cross-correlation analysis and mediational analysis) found a relationship between TL and recovery and that these components influence each other both on the same day and on the next one. Conversely, some studies have shown that HI and TQR do not influence RPE and physical enjoyment (98). Interestingly, Rossi et al. (2022) (97) highlighted the significant limitations of previous studies as they used an analytical approach most suitable for mono-dimensional (i.e., they use just one variable at a time without fully exploiting the complex patterns underlying the available data). However, practitioners may have an increasing amount of data that is difficult to translate into useful information. For this reason, machine learning approaches have grown rapidly since the last decade (23, 105). These approaches could help to have a complete overview of players' wellness, providing accurate predictions and valuable insights about injury risks (97, 105, 106). Rossi and colleagues (2022) found that it is possible to accurately estimate the well-being index of players based on their workload history and, in particular, from the aggregation of chronic feature (exponentially weighted average of the training workloads of the previous 28 days) (97).

The following sections will provide practical examples related to our conceptual framework for understanding the complex relationship between TL, physical performance, fitness status, and fatigue in soccer.

6. PRACTICAL EXAMPLES

6.1. Relationship Between Physical Performance, Training Load, Fitness Status: Practical Examples

Table 1.1 shows two practical examples of differences between TL, physical performance, and fitness status. Based on the revised TL and performance frameworks, considering HSR distance as EL and RPE as IL indicators, it is possible to detect the differences between the two athletes. Given the same training session duration, if athlete B achieves a greater HSR distance with a higher RPE value than athlete A, both EL and IL (calculated as the product of the training duration and external/internal indicators) will be higher for athlete B. However, the total amount of HSR distance does not explain intensity (a concept closely related to performance) or fitness status. In this way, we calculated the intensity based on match demand performance by relating the volume to the unit of time (i.e., HSR per minute). At the same time, the fitness status was obtained through the EL/IL ratio. Example 2 explains that two athletes may differ in TL, physical performance, and fitness status considering the different training session time. Indeed, even if athlete B presents a higher TL, athlete A shows greater intensity (derived from match demand indicators) and higher fitness status. Accordingly, athlete A performed better than athlete B, also presenting higher fitness levels.

6.2. Relationship Training Load and Fitness Status: Practical Examples

Table 1.2 shows the relationship between TL and fitness status (calculated as EL/IL ratio), considering four different examples. Concerning TL calculations, we employed both external and internal, as suggested by Impellizzeri and colleagues (30). Moreover, we implemented a new operationalization of TL, simply by multiplying EL and IL (i.e., $EL \cdot IL / 100$) to estimate the total load. We highlighted that, to date, there are still no validated formulas in the literature to determine the total load (considering both the internal and external indicators). Accordingly, this approach represents a simple calculation attempt. The examples in Table 1.2 show the difference between TL and fitness status in two athletes performing the same specific exercise (e.g., SSG). Based on the

operationalization of EL and IL, it is possible to observe that an athlete can have higher TL but lower level of fitness and vice versa (examples 1 and 2). The implementation of EL and IL is necessary to fully understand the effects of training.

6.3. Training Load Assessment: could a single indicator provides an appropriate and complete overview of it?

The main objective of our revised TL framework was to develop an expanded version of the previous one that could help practitioners improve decision-making related to the monitoring process. As reported above, specify the concepts of “volume” and “intensity” combined with external (related to match-demand) resulted in two further subdivisions (i.e., external load volume [ELV], external load intensity [ELI]) (Figure 1.2).

Table 4 shows the relationship between (TL) and Match load considering ELV and ELI based on framework carried out by Impellizzeri et al (30). These examples highlighted that practitioners should consider more than one indicator to understand the percentage of work completed in training compared to the match as suggested by the framework carried out by Pillitteri et., al. (32). Indeed, the exclusive application of a single type of indicator (i.e., referring to either the volume or the intensity) would provide partial information relating to the TL compared to the competition (reference measures) (32). Moreover, an overview of the TL can be given using more than one indicator (both related to volume or intensity). In fact, given the complexity of soccer physical performance, indicators related to distance, accelerations, and metabolic power should be included. It is worth noting that, in the era of “big data,” the huge number of indicators and “numbers” could lead confusion among practitioners limiting the decision-making processes. In this way, artificial-intelligence related approaches such as principal components analysis (PCA) are widely used in sports as a multivariate technique to manage big data with the aim of reducing data used in sports to identify key performance indicators (107). In this way, sports scientists, and researchers to select and extract the variables that explain a high percentage (>70%) of the total variance of physical, physiological, technical, or tactical data that explain the performance have thought the PCA technique.

Table 1.4 shows a practical example of the differences between EL and IL indicators used to assess the physical performance in soccer. Using external indicators such as HSR distance to evaluate the difference between two athletes (i.e., which athlete exhibits the best physical performance), it is possible to assess the performance (match-demand) considering the “time” factor. Even if athlete A

completed a greater HSR distance (500m) compared to athlete B (300m), the latter completed this distance in a shorter time. Consequently, by calculating the HSR distance per minute, it is possible to establish that athlete B performed better than athlete A. Conversely, when IL indicators are used, the opposite situation occurs (i.e., athlete A shows a better performance index (given by the EL/IL ratio) than athlete B by using “volume” indicators (i.e., time and HSR distance). Athlete A responds to the activity performed with a lower average HR suggesting a better fitness status. It is worth noting that athlete B showed higher physical performance (athlete-related) calculating EL/IL ratio by using the HSR distance per minute indicator. Moreover, through this example, we also found that athlete A has a higher “TL” but a lower physical performance based on both match-demand (HSR distance per minute) and athlete-related (calculated with HSR distance per minute).

This example indicates that it is necessary to assess athlete’s physical performance using both EL and IL indicators (considering both “volume” and “intensity” indicators).

7. LIMITATIONS AND FUTURE DIRECTIONS

A qualitative approach was used for this review which may lead to bias related to the researchers’ knowledge. Our revised framework has reanalysed some concepts derived from previous frameworks, studies and theories related to training and its process. Moreover, the field experience and reasoning provided the basis for modifying and clarifying the previous frameworks. Our frameworks need experimental studies for further verification and explanation as the investigated phenomena result in complex and interconnected factors that could lead to misinterpretations among practitioners.

We have tried to provide practical examples, further definitions, explanations regarding while no theories or completely new conceptual structures have been presented. Moreover, although the implementation of EL/IL ratio represent a useful and simple approach to understand the athlete’s fitness status, practitioners should be aware about some intrinsic limitation behind the main IL metrics available in soccer (i.e., RPE and HR). Moreover, soccer performance derives by the complex interaction between factors such as technical, tactical, physical, psychological, cognitive, and emotional component. However, we highlight that our framework focuses exclusively on the physical performance aiming to provide a clear conceptualization (often overlooked or confused by professionals) about two main pillar (i.e., match- demand performance and physiological-demand performance) we have identified in relation to performance analysis and TL. Accordingly, we are

aware that the underrepresentation of other soccer performance factors such as technical-tactical and cognitive representing a possible limitation about our framework.

As concerning the intensity concept, we highlight that it can be understood through indicators such as sprint (distance or number) per minute. This approach lacks the possibility to know the recovery between two or more sprints (i.e., sprint bouts) and cannot be established in a daily monitoring process performed in a real word scenario. Accordingly, this factor has not been included in our framework representing a possible limitation.

8. PRACTICAL APPLICATION

In developing this narrative review, existing frameworks and models were considered (i.e., Jeffries et al., 2022, Impellizzeri et al., 2019 and Gabbett et al., 2017) but focused on the complex and related concepts such as physical performance, TL, fitness status, and fitness-fatigue reporting definitions and providing practical applications through examples.

As concerning the concept of physical performance, our framework revealed three main components. In detail, the “Soccer Physical performance,” was defined and expanded on which has been divided into “match-demand performance,” “physiological-demand performance,” and “athlete-related performance.” This lead that different aspects of physical performance in soccer should not be overlooked. Consequently, both researchers and “field” professionals should distinguish these different aspects to evaluate physical performance in soccer.

In soccer, to evaluate the physical components of both load and performance it seems necessary to consider both the components related to match-demand and the physiological aspects, including volume and intensity indicators. Practitioners can refer to this framework of physical performance to provide valuable and reliable information regarding the assessment of both training and soccer match. In this way, the coaches (technical staff) will be able to understand which player will have obtained the best or worst physical performance as well as calculate TL appropriately based on the different perspectives conceptualized in this study. Furthermore, the use of both volume and intensity indicators (including both external and internal) was encouraged for a complete determination of the TL, underlining that the correct calculation of the TL considers the "duration" factor (88).

This review reported a revised TL framework by considering two constructs relating to the EL referring to “volume” and “intensity,” which are combined with external (related to match-demand) resulting in two calculation options as follows: external load volume (ELV), external load intensity (ELI). As the TL result from the product of volume and intensity, each EL indicator should be multiplied by time to calculate ELV or ELI.

The practical examples provided to support our framework allow researchers and practitioners to highlight the complex relationships between EL, IL, and athlete physical performance, providing further insight into soccer players monitoring and training prescription. The determination of both the TL and the physical performance cannot presuppose the use of multiple indicators relating to EL and IL, considering the “time” factor as essential for this purpose.

Given the complexity of concepts related to soccer physical performance, TL, fitness status and fatigue-recovery process, we provided conceptual framework, definitions, and practical applications to understand meaning, relationship, differences, and connections.

To reach this propose, we modified previous frameworks by explaining and adding new constructs for conceptualizing soccer physical performance, TL, and fitness status with the aim of aiding the development, implementation, and interpretation of the measures used for the monitoring of athletes in a real soccer context.

Table 1, Concept or construct definitions and explanations			
Label/concept/construct	Definition	What does it measure?	How can it be measured?
Performance	Performance can be defined as the accomplishment of goals by meeting or exceeding predefined standards (44)	Assess how much ‘work’ someone has performed compared to a gold standard	Trough different indicators related to the aim of performance (i.e., what kind of performance has been considered).
Soccer Performance	Soccer performance is the result of the interaction between technical, tactical, cognitive, psychological and physiological factors.	Assess how much ‘work’ an athlete has performed compared to a gold standard (i.e., match demand or physiological factors)	Technical, tactical, cognitive, physical, psychological indicators
Physical soccer performance	Performance can be defined as the accomplishment of goals by	Assess how much ‘physical work’ an athlete has	Trough different indicators related

	meeting or exceeding predefined standards related to physical components.	performed compared to a gold standard (i.e., match-demand or physiological-demand)	both external (imposed match-demand), internal (physiological response to a given imposed stimulus) factors and EL/IL ratio (athlete performance)
Match-demand Performance	Athlete or team activity performed during a drill, a training session or a match compared to the reference's values	Assess how much 'physical work' an athlete does in the training, match or competition compared to the reference's values	External indicators (e.g., speed, distance, accelerations, metabolic power)
Physiological-demand performance	Physiological responses of the athlete recorded during a drill, a training session or a match compared to the reference's values	Psychophysiological athlete responses in the training, match or competition compared to the reference's values	Internal indicators (e.g., HR, VO2, RPE)
Athlete-related performance	Physiological athlete responses to a given EL compared to reference's values	Individual athlete internal responses to a given EL	EL/IL ratio
Training Load	Input variable that is manipulated to elicit the desired training response (108)	Load: the amount of work performed by someone.	External indicators (related to match-demand) Internal indicators: (related to psychological-demand)
External Load	Objective measure of the work that an athlete completes during training or competition	External Load Volume: the total amount of work performed External Load Intensity: the amount of work performed in the unit of time (minutes)	External indicators (related to match-demand) - External volume indicators - External intensity indicators
Internal Load	Actual psychophysiological response that the body initiates to cope with the requirements elicited by the external load.	Physiological athlete internal response as a consequence of external activity performed	Internal indicators (e.g., HR, VO2, RPE)

Fitness Status	The ACSM defines fitness as “a set of attributes that people have or achieve that relates to the ability to perform physical activity” (91)	How the athlete response to the Load (i.e., Factors related to athlete’s response to a given performed external Loads)	EL/IL ratio
Load Response (Load Tolerance)	Psychophysical athlete’s answer or reaction to External and/or Internal Load (i.e., match or training)	How the athlete is coping with the Load (i.e., Factors related to athlete’s Fitness-Fatigue status and recovery capability)	Relationship between Wellness scale and Load
Readiness	Willingness or a state of being prepared for something (Cambridge dictionary). Optimal player readiness is a condition where an athlete has no impairment of physical performance, no mental fatigue or excessive psychological distress, and which represents “the athlete’s capacity to complete training activities and perform during competition” (109).	Whether the athlete is physically and/or mentally prepared for exposure to another training stimulus (i.e., readiness to train/compete). Readiness represents a state of preparedness (assessed at a specific moment in time) deriving from a combination of stressors (positive or negative) (27).	Assessment of muscular strength, endurance, HR variability (HRV), and cognitive function. Tracking various physiological (eg, using saliva and blood tests) and psychological factors such as sleep, muscle soreness, stress levels, and mood, among others (27). Relationship between Wellness scale and neuromuscular functions (i.e., Field and Laboratory Test or GPS assessment)
Fatigue	(1) Failure to maintain the required or expected force (or power output) (110). (2) An inability to complete a task that was once achievable within a recent time frame (111). (3) Complex construct that can be interpreted in terms of an acute	The degree of physiological or psychological fatigue and tiredness	Physiological assessment (i.e., laboratory analysis or field test) Self-report questionnaire (e.g., TQR). Relationship between Wellness scale and Load

	reduction in muscle force/power, higher perception of effort, task failure, a mood dimension or as a symptom of disease, depending on the context (112).		

Table 1.1, Relationship between Training Load, Performance, and Fitness Status on soccer training session				
EXAMPLE 1	ATHLETE A		ATHLETE B	
	ST: 80'		ST: 80'	
	External indicators HSRD: 500m	Internal indicators RPE: 7	External indicators HSRD: 800m	Internal indicators RPE: 8
	TRAINING LOAD: AU EL: based on HSRD: (ST) 80* (HSRD) 500=40.000 AU IL: based on RPE: 7x80= 560 AU		TRAINING LOAD: AU EL: based on HSRD: (ST) 80* (HSRD) 800=64.000 AU IL: based on RPE: 8x80=640 AU	
	INTENSITY (MATCH- DEMAND PERFORMANCE) Calculate the amount of HSRD based on Session Time (meter*minute): 500m in 80'= 6,25 m/min		INTENSITY (MATCH- DEMAND PERFORMANCE) Calculate the amount of HSRD based on Session Time (meter*minute): 800m in 80'= 10 m/min	
	ATHLETE PERFORMANCE INDEX (FITNESS STATUS) Based on EL/IL ratio 40.000/560= 71,4		ATHLETE PERFORMANCE INDEX (FITNESS STATUS) Based on EL/IL ratio 64.000/640=100	
	Outcome: considering the same session time (i.e., 80'): Athlete B presents (1) higher training load (both external and internal), (2) greater performance (match-demand) and (3) higher athlete-related performance (fitness status) than Athlete A			
EXAMPLE 2	ATHLETE A		ATHLETE B	
	ST: 60'		ST: 90'	
	External indicators HSRD: 500m	Internal indicators RPE: 5	External indicators HSRD: 500m	Internal indicators RPE: 8
	TRAINING LOAD: AU EL: based on HSRD: (ST) 60* (HSRD) 500=30.000 AU IL: based on RPE: 5x60= 300 AU		TRAINING LOAD: AU EL: based on HSRD: (ST) 90* (HSRD) 500=45.000 AU IL: based on RPE: 8x90= 720 AU	
	INTENSITY (MATCH- DEMAND PERFORMANCE) Calculate the amount of HSRD based on Session Time (meter*minute): 500m in 60'= 8,3 m/min		INTENSITY (MATCH- DEMAND PERFORMANCE) Calculate the amount of HSRD based on Session Time (meter*minute): 500m in 80'= 5,5 m/min	
	ATHLETE PERFORMANCE INDEX (FITNESS STATUS) Based on EL/IL ratio		ATHLETE PERFORMANCE INDEX (FITNESS STATUS) Based on EL/IL ratio	

	30.000/300=100	45.000/720=62,5
Outcome: considering different session time (i.e., 60' and 90'): Athlete B presents (1) higher training load (both external and internal); (2) lower performance (match-demand) and (3) lower athlete-related performance (fitness status) than Athlete A, highlighting the decoupling between the player's training load, performance and fitness status.		
Legend: ST: session time; HSRD, high-speed running distance (>20 Km/h); RPE, rating of perceived exertion; EL, external load; IL, internal load;		

Table 1.2, Relationship between Training Load (external, internal and Total) and Fitness Status (calculated as external/internal load index) on soccer specific HIIT drill				
SOCCER SPECIFIC DRILL (HIIT FORMAT: SMALL SIDED GAMES)				
Small Sided Games (SSG) Format: 5VS5 Pitch size: 30X28m Duration: 10'				
	ATHLETE A		ATHLETE B	
EXAMPLE 1 Same EL Different IL	External indicators MP: 13 w TLE: 13 * 10= 130 AU	Internal indicators RPE: 6 TLI: 6 * 10= 60 AU	External indicators MP: 13 w TLE: 13 * 10= 130 AU	Internal indicators RPE: 8 TLI: 8 * 10= 80 AU
	Total Load: TLE * TLI/100 (130 * 60)/100= 78 AU		Total Load: TLE * TLI/100 (130 * 80)/100= 104 AU	
	ATHLETE PERFORMANCE INDEX (FITNESS STATUS): (TLE/TLI) *10 (130/60) * 10= 21,6 AU		ATHLETE PERFORMANCE INDEX (FITNESS STATUS): (TLE/TLI) *10 (130/80) * 10= 16,2 AU	
	Outcome: Athlete B presented higher training total load than athlete A; Athlete A shows higher fitness status			
EXAMPLE 2 Different both EL and IL (Athlete A has higher EL than B Athlete B has higher IL than A)	External indicators MP: 16 TLE: 16 * 10= 160 AU	Internal indicators RPE: 6 TLI: 6 * 10= 60 AU	External indicators MP: 13 TLE: 13 * 10= 130 AU	Internal indicators RPE: 8 TLI: 8 * 10= 80 AU
	Total Load: TLE * TLI/100 (160 * 60)/100= 96 AU		Total Load: TLE * TLI/100 (130 * 80)/100= 104 AU	
	ATHLETE PERFORMANCE INDEX (FITNESS STATUS): (TLE/TLI) *10 (160/60) * 10= 26,6 AU		ATHLETE PERFORMANCE INDEX (FITNESS STATUS): (TLE/TLI) *10 (130/80) * 10= 16,2 AU	
	Outcome: Athlete B presented higher training total load than athlete A; Athlete A shows higher fitness status			
EXAMPLE 3 Different both EL and IL	External indicators MP: 13 TLE: 13 * 10= 130 AU	Internal indicators RPE: 6 TLI: 6 * 10= 60 AU	External indicators MP: 16 TLE: 16 * 10= 160 AU	Internal indicators RPE: 8 TLI: 8 * 10= 80 AU

Athlete B has higher EL and IL than A	Total Load: $TLE * TLI/100$ (130 * 60)/100= 78 AU		Total Load: $TLE * TLI/100$ (160 * 80)/100= 128 AU	
	ATHLETE PERFORMANCE INDEX (FITNESS STATUS): $(TLE/TLI) * 10$ (130/60) * 10= 21,6 AU		ATHLETE PERFORMANCE INDEX (FITNESS STATUS): $(TLE/TLI) * 10$ (130/80) * 10= 26,6 AU	
	Outcome: Athlete B presented higher both training total load and fitness status			
EXAMPLE 4 Different EL Same IL	External indicators MP: 13 TLE: 13 * 10= 130 AU	Internal indicators RPE: 8 TLI: 8 * 10= 80 AU	External indicators MP: 16 TLE: 16 * 10= 160 AU	Internal indicators RPE: 8 TLI: 8 * 10= 80 AU
	Total Load: $TLE * TLI/100$ (130 * 80)/100= 104 AU		Total Load: $TLE * TLI/100$ (160 * 80)/100= 128 AU	
	ATHLETE PERFORMANCE INDEX (FITNESS STATUS): $(TLE/TLI) * 10$ (130/80) * 10= 16,2 AU		ATHLETE PERFORMANCE INDEX (FITNESS STATUS): $(TLE/TLI) * 10$ (160/80) * 10= 26,6 AU	
	Outcome: Athlete B presented higher both training load and fitness status			
Legend: HIIT, high intensity interval training; EL, external load; IL, internal load; MP, metabolic power; TLE, external training load; RPE, rating of perceived exertion; TLI, internal training load				

Table 1.3, Relationship between Training (TL) and Match load (ML) considering external load volume (ELV) and external load intensity (ELI)		
EXTERNAL LOAD VOLUME	MATCH	TRAINING SESSION
EXAMPLE 1	MT: 90'	ST: 110'
	External Volume indicators TD: 13 Km	External Volume indicators TD: 8 Km
	MATCH LOAD: AU EL: based on TD 90 (MT)* 13 (TD)=1170 AU	TRAINING LOAD: AU EL: based on TD 110 (ST)* 8 (TD)=880 AU 75% OF MATCH LOAD
EXAMPLE 2	MT: 90'	ST: 100'
	External Volume indicators n°acc, 50	External Volume indicators n°acc: 70
	MATCH LOAD: AU EL: based on n°acc 90 (MT)* 50 (n°acc)=4500 AU	TRAINING LOAD: AU EL: based on (n°acc) 100 (ST)* 70 (n°acc)=7000 AU 155% OF MATCH LOAD
EXTERNAL LOAD INTENSITY	MATCH	TRAINING SESSION

EXAMPLE 1	MT: 90'	ST: 110'
	External Intensity indicators TD: 13Km TDmin: 144m/min	External Intensity indicators Total Distance: 8Km TDmin: 72m/min
	MATCH LOAD: AU EL: based on TDmin $90 (MT) * 144 (TDmin) = 12960 \text{ AU}$	TRAINING LOAD: AU EL: based on TDmin $110 (ST) * 72 (TDmin) = 7920 \text{ AU}$ 61% OF MATCH LOAD
EXAMPLE 2	MT: 90'	ST: 100'
	External Intensity indicators n°acc: 50 (n°acc/min): 0,5/min	External Intensity indicators n°acc: 70 (n°acc/min): 0,7/min
	MATCH LOAD: AU EL: based on n°acc $90 (MT) * 0,5 (n°acc/min) = 45 \text{ AU}$	TRAINING LOAD: AU EL: based on (n°acc) $100 (ST) * 0,7 (n°acc/min) = 70 \text{ AU}$ 155% OF MATCH LOAD
Legend: MT, match time; ST, session time; TD, total distance; EL, external load; n°acc, n° of intense accelerations; TDmin, total distance per minute; n°acc/min, n° of intense accelerations per minute; TD, total distance;		

Table 1.4 Differences between external and internal indicators to assess soccer performance	
TRAINING MONITORING BASED ON EXTERNAL INDICATORS (MATCH-DEMAND PERFORMANCE)	
ATHLETA A	ATHLETE B
TIME: 10' HSRD: 500m MATCH-DEMAND PERFORMANCE HSR/TIME HSR/MIN= 50 TRAINING LOAD: $500 * 10 = 5000 \text{ AU}$	TIME: 5' HSR: 300m MATCH-DEMAND PERFORMANCE HSR/TIME HSR/MIN= 60 TRAINING LOAD: $300 * 5 = 1500 \text{ AU}$
OUTCOME: ATHLETE B presented higher performance (match-demand) than ATHLETE A	
TRAINING MONITORING BASED ON INTERNAL INDICATORS (PHSYOLOGICAL-DEMAND PERFORMANCE)	
ATHLETA A	ATHLETE B
TIME: 10' AVG HR: 160 bpm TRAINING LOAD: $160 * 10 = 1600 \text{ AU}$ ATHLETE PERFORMANCE INDEX (FITNESS STATUS) BASED ON TOTAL TIME $(10/160) * 100 = 6,25\%$ BASED ON TOTAL HSRD $(500/160) = 3,12$ BASED ON HSRD PER MINUTE $(50/160) * 100 = 31,25\%$	TIME: 5' AVG HR: 180 bpm TRAINING LOAD: $180 * 5 = 900 \text{ AU}$ ATHLETE PERFORMANCE INDEX (FITNESS STATUS) BASED ON TOTAL TIME $(5/180) * 100 = 2,7\%$ BASED ON TOTAL HSRD $(300/180) = 1,6$ BASED ON HSRD PER MINUTE $(60/180) * 100 = 33,3\%$
OUTCOME: ATHLETE A presents a better performance (athlete-related) than ATHLETE B	
Legend: HSRD, high-speed running distance; HR, heart rate.	

Note: the examples show that there is a different meaning of performance determined by the different approach considered (i.e., based on either *match-demand* or *athlete-related*). Indeed, considering *match-demand* performance approach, athlete B present higher performance than athlete A while considering *athlete-related* performance approach, athlete A performs better than athlete B by using “volume” indicators (i.e., time and HSRD). Athlete B shows higher performance (athlete-related) calculating EL/IL ratio by using HSRD per minute indicator.

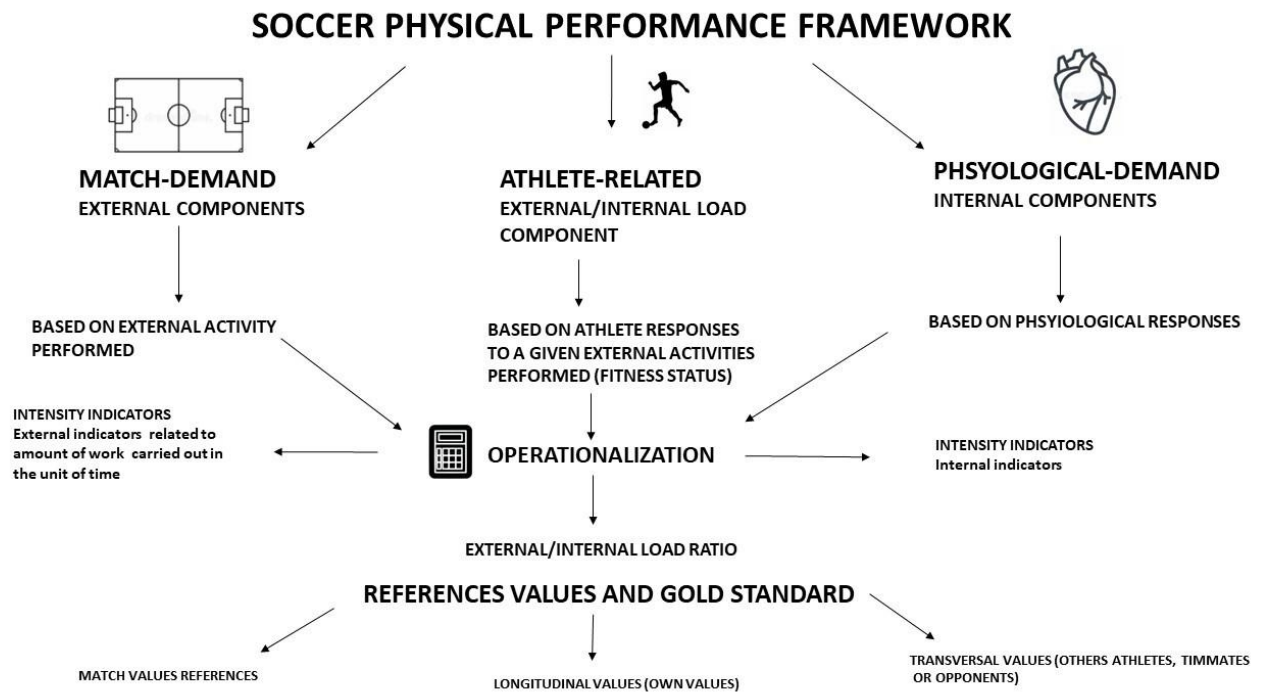


Fig. 1 Soccer physical performance framework. Note: Physical soccer performance has been conceptualized through 3 components as follow: (1) *match-demand* (i.e., an external component such as distance, speed, accelerations, metabolic power, change of directions, strength); (2) *physiological-demand* (internal component such as HR, maximal oxygen consumption, rate of perceived exertion); (3) *athlete-related performance* refers to an individual internal response to a given EL. *Match demand* is operationalized through “intensity” external indicators, *physiological-demand* using internal indicators, and EL/IL ratio to obtain *athlete-related performance*. In this case, “performance measures” cannot disregard the idea of “comparison.” Each value obtained should be compared with a reference value. In detail, the meaning of performance can be obtained through a longitudinal assessment, transversal assessment, and the external activity of the match-demand (i.e., gold standard).

SOCCER PHYSICAL PERFORMANCE FRAMEWORK PRACTICAL EXAMPLE

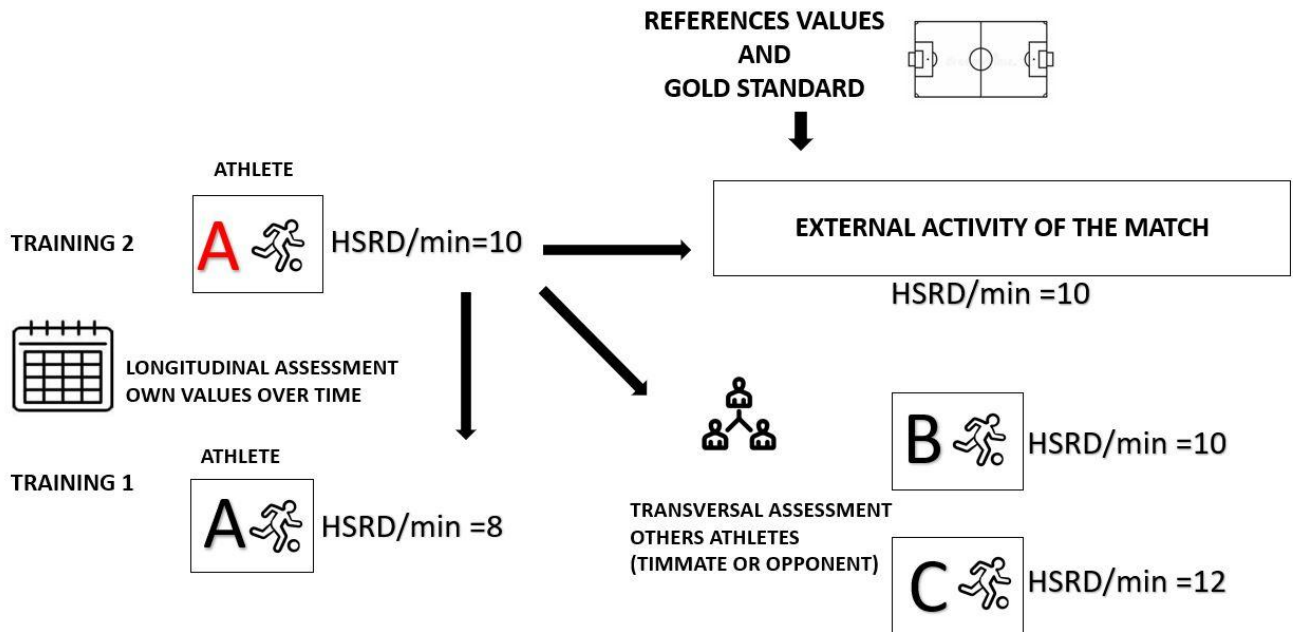


Fig. 1.2 Soccer physical performance framework: a practical example. Note: we have provided an example related to the meaning of physical soccer performance. In training 2, athlete A performed the same high-speed running distance (HSR) compared to the gold standard (i.e., match-demand references values); athlete A performed more HRSD than their previous activity (i.e., longitudinal assessment); athlete A performed the same HRSD than athlete B and less than athlete C (i.e., transversal assessment).

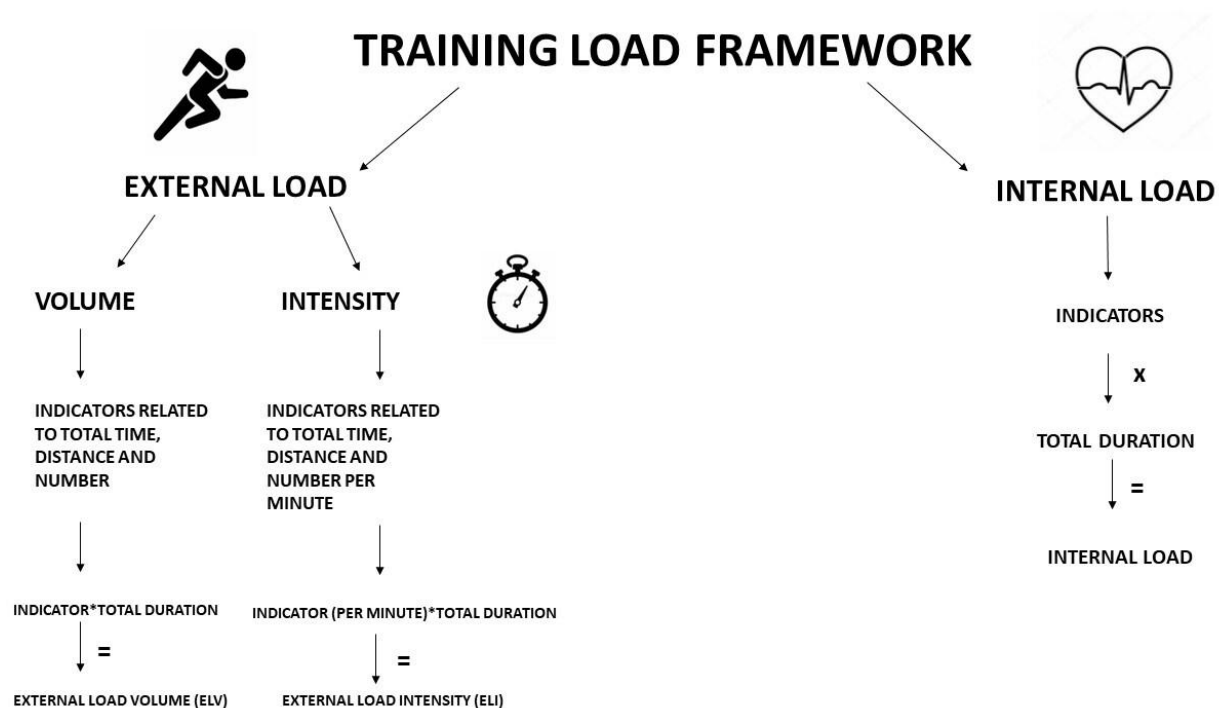


Fig. 1.2 Training load framework. Note: In Training Load framework, we have considered the previous “training load framework” carried out by Impellizzeri (2019). We have provided examples and practical applications reporting two constructs related to the “volume” and “intensity” dimensions to the “external load”. We have operationalized “external load volume” (ELV) and “internal load intensity” (ILI). Volume refers to the total amount of work carried out in a given period. The amount of work carried out in the unit of time (e.g., distance per minute or number of intense accelerations per minute) can be considered as a measure of “intensity.” The training load results from volume and intensity; therefore, each indicator must be multiplied by time to calculate ELV or ELI. We have operationalized ELV and ILI by multiplying the relative indicator by the duration. For example, ELV is obtained by multiplying the total distance (TD) by the duration (exercise, training session, or competition). At the same time, ILI is calculated by multiplying the total distance per minute and total duration (exercise, training session, or competition). Internal load is obtained by multiplying the indicator (e.g., RPE or HR) by total duration (exercise, training session, or competition).

1.3 Injury in soccer: from risk factors to prevention strategies

Injury has been considered as “any physical complaint sustained by a player that results from a football match or football training, irrespective of the need for medical attention or time loss from football activities” (113). In 2006, Fuller et al. published a consensus statement (113) about soccer injuries due to the many definitions and methodologies used among studies, which led to conflicting results, confusion, and difficulty comparing studies. Authors provided recommendations on how the incidence of injuries should be reported to avoid methodological issues between studies comparison (113). However, a comprehensive football-specific extension (upgraded from the previous consensus

statement) has provided the methodology and definitions that ensure more consistent study designs, data collection procedures and use of nomenclature in future epidemiological studies of football injuries and illnesses regardless of setting (114).

Soccer injuries represent one of the most relevant problems researchers have extensively studied as they have significant negative repercussions both on the health of players and the financial burden of the clubs (115, 116). Epidemiological studies have reported that soccer results in high injury incidences at professional, amateur, and young levels (117-120). Overall, the incidence of injuries in male professional soccer players is 8.1 injuries/1,000 hours of exposure (121). Considering both professional and amateur levels (12.5/1,000 h), the incidence of injuries is higher in matches than in training sessions, involving the lower extremity with the highest incidence rates (121, 122). Specifically, hamstring strain injury (HSI) is the most prevalent non-contact injury reported in professional male soccer (12–14 % of all injuries (115)), accounting for 37 % of all muscle injuries sustained (116, 123). Furthermore, the reinjuries rate of HSIs ranges from 16–60 % (123). In contrast, anterior cruciate ligament (ACL) injuries are considered among the most severe, with a time loss of 185-256 days per injury (124). Walden et al., 2016 have found that the overall ACL injury rate was 0.066 per 1,000 h or 0.43 per team per season, highlighting an increase in the number of annual ACL injuries from 1996 to 2012 (125). It is worth noting that most knee and ACL injuries occurring in non-contact situations point to a gap between research and practice in existing evidence-based prevention programmes, emphasising the need to implement them (125). Moreover, ACL injuries present a high rate of recurrence (126). Ekstrand et al., 2011 (118), have reported that players can result in a mean of 14 competition days lost per injury (range 1–128 days), causing serious damage to the team performance and negatively affecting the financial burden (127) on the players and their clubs (127). For example, the mean cost of an injured player in a professional team has been reported as 500.000€/month (128).

The high magnitude of the injury phenomenon can be attributed to numerous factors (multifactorial aetiology (129-131)), including the high intensity of play which has increased over the years, and the high number of matches played during the season. In light of this, there is a need to improve injury prevention strategies across all age groups and performance levels. However, several studies have investigated the relationship between soccer injuries and workload. In a review by Jasper (2017) (21) reported scarce evidence regarding the relationship between external and internal load and injury or illness. However, given the extreme complexity of these factors (i.e., training load and injuries), the literature shows controversial results. Nevertheless, every athletic injury occurs while athletes are exposed to training and competitor workloads regardless of the interaction between risk factors or

inciting the biomechanical event and lack of direct causality (132). Accordingly, the workload is one of the main factors that should be considered in injury prevention strategies. In the third chapter we will report a brief review with conceptual framework focusing on hamstring injury and we delve into the role of Data-Informed Approach to support practitioners in protecting players.

In the next section, we will intensely discuss the implication of load on injuries. A detailed and exhaustive treatment of soccer injuries and its relative prevention strategies such as strength training, that literature as well as practitioners considered as a “must” in this topic, is outside the scope of this thesis.

1.5 Implication of Machine Learning in soccer

In the last twenty years, the technology development has exponentially increased leading us the production of a large amount of data obtained from different devices such as Electronic Performance and Tracking Systems (EPTS). In this way, the term “Big Data” has been coined by John Mashey in 1990s. It was defined as large datasets so large and complex that it is hard to analyse using “standard” data processing and most common statistical software (133). Hence, Big Data requires specific techniques and technologies able to reveal insights from huge datasets that are diverse, complex, and of a massive scale (134). Traditional statistics is considered inadequate to analyse these large amounts of data due to complexity. Indeed, based on different input variables, practitioners are often interested to understand relationship, implication association of such variables and outcomes of interest. For example, in the soccer context, starting from Training Load indicators (from which drive a huge amount of data), studies have investigated different outcomes such as physical performance and injury. The innovative technology of the Big Data offers a new way to extract insight from the myriads of data that that overwhelms us. The ability to manage and extract information from big datasets permits to have advantages on competitors. In particular, accuracy in the predictive model created from historical evidence may lead to take more focused-on decision-making. The “bang” of available data is increasing in all research fields including soccer context, producing what is call Data Science (135). Data Science aims to extract knowledge from data by interdisciplinary fields such as mathematics, statistics and computer science (i.e. probability models, machine learning, statistical learning, data mining, pattern recognition, artificial intelligence and high performance computing) (136). The development of machine learning applied on big datasets has

enhanced the growth and importance of Data Science. Machine learning focuses on pattern recognition and computational learning theory in artificial intelligence (AI). This methodology aims to create algorithms that can learn and make predictions on Big Data (137). In particular, Machine Learning has been defined by Herbert Simon, who won the Nobel Prize in Economics in 1978, as “computer programs that automatically improve their performance through experiences”. As a matter of fact, it is a subfield of Computer Science focused on the study of pattern recognition and computational learning theory in artificial intelligence (137) while Peter Flach defines Machine Learning as something “...all about using the right features to build the right models that do the right job” (137). The features are considered the individual measurable properties of the phenomenon being observed. To develop a useful algorithm in pattern recognition, classification, and regression it is necessary to choose accurately the features typologies (i.e. dependent and independent). Moreover, data scientist aims to solve problem (i.e. task) through the features while the model is the output produced by the machine learning algorithm applied on training. Accordingly, the selection of the correct model to solve our task is the second crucial aspect to define a machine learning algorithm. Machine learning algorithms are classified into two categories in accordance with the task that we want to solve.

- 1) Supervised machine learning algorithms aim to map function able to predict output features (y) based on input ones (x): $Y=f(x)$

They are called supervised because the process created to define an algorithm learns from a labelled dataset. In particular, these machine learning processes create algorithms able to discriminate labels (y) from the training datasets (x).

Supervised machine learning problems could be further classified into two subgroups:

- Regression problems, when the output features are continuous, such as blood oxygenation, lactate, power or one maximum repetition.
- Classification problems when the output features are categorical such as injury/no injury, goal/no-goal or male/female.

- 2) Unsupervised machine learning algorithms aim to create models from the distribution of input data (x) to obtain information about them. As a matter of fact, unsupervised dataset has only input features (x) without corresponding output one (y).

Like supervised machine learning problems, Unsupervised machine learning problems could be further classified into two subgroups:

- Clustering problems, when it is necessary to discover subgroups in the dataset, such as grouping athletes by training/physiological characteristics.
- Association rules learning problems, when it is necessary to discover rules describing a large part of the dataset, such as athletes that when performing a particular training (e.g. high intensity resistance training) also perform a particular stretching modality (e.g. ballistic stretching).

One of the main applications of machine learning in soccer concerns the injury topic. Indeed, studies have investigated the relationship between some input variables (features) such as Training Load, Wellness, Recovery as well as Player Profile, Body Composition and Physical Assessment and injuries.

As concern the Machine learning Models, Supervised Machine Learning models can learn a function that map an input (e.g., external workloads, internal workloads, and self-reported wellness) to an output (e.g., injury label). The most common supervised machine learning models used for injury forecasting are decision trees, binary logistic regression, random forests, and supporting vector machines. Moreover, as reported by Vallance et al. [24] also trained KNearest Neighbours, Linear Discriminant Analysis, Ridge classifier, Gaussian Naive Bayes classifier, multi-layer perceptron and eXtreme gradient boosting algorithms. The injury prediction Models need to be validated to compare the own prediction performance with different baseline models (dummy classifiers [models that make predictions without trying to find patterns in the data by using naïve rules]). Indeed, similar performance results among the own model and the dummy models suggest that the own framework of data analytic is not able to detect patterns in data for an accurate prediction.

Train and Set

Validation

To assess the goodness of the machine learning model, the dataset was usually split into three different datasets. In the first step, the model is initially fit on a *training dataset* (a set of examples used to fit the parameters). Successively, the model prediction goodness is validated on a *validation set* while tuning the model's hyper-parameters. Finally, the *test set* is a dataset used to provide an unbiased evaluation of the final model. The most common approach used to validate the injury forecasting is the *10-fold cross-validation approach*. In the cross-validation approach, the

dataset is repeatedly split into training and validation sets. An additional test set, is required for validating the model's performance to hold out from cross-validation. In order to be noticed in the cross-validation approach, a stratified split method is required to balance the distribution of the classes between folds (i.e., the distribution of the classes in each fold have to follow the one found in the entire dataset). For example, Rossi et al. [15], trained and validated their models by week n , while testing them in the week $n + 1$. In contrast, Carry et al. [22] trained and validated their models in season, and tested the fitted model in the following season. By using an evolutive scenario, as proposed in [15], it is possible to test the ability of the classifiers to predict injuries in new data that are not already present in the dataset where the machine learning models are trained and validated. Indeed, by using the validation approach proposed by Rossi et al. [15] it is possible to re-train models inserting new injury and no-injury examples as the season goes by increasing the sample size as the season continues.

Data Processing for Each Training Fold

A data preprocessing phase is required for each training fold in both cross-validation and evolutive scenario approaches. In the first step, a sampling approach is useful for balancing the target classes, as the number of injury examples is extremely lower than the no-injury ones. Moreover, a feature selection process must be implemented to selecting the best features and predict injuries aiming to reduce features space and consequently improve the interpretability of the machine learning model.

Sampling

Over- and under- sampling in data analysis are techniques to adjust the class distribution of a dataset. Oversampling permits to increase in the sample size of the minority class, while under-sampling reduces the number of examples of the majority class to balance the two classes. In a real word scenario, the injury dataset usually shows only 2% of injury examples over the total number of observations, an over-sampling approach is needed to balance the two classes. *Synthetic minority over-sampling technique (SMOTE)* is the most common approach, to increase in the injury prediction goodness compared to models trained without oversampling process. This approach considers k nearest neighbours of a current data point in the multidimensional feature space. It is worth noting that the oversampling process should be performed only on the training set in order to avoid any possible risk of overfitting. In fact, the examples created by oversampling techniques creates examples based on similarity of injury cases in the dataset and, consequently, it will create “fake” examples that are similar to the real ones. Hence, if such synthetic examples are created based on the

entire dataset (before performing the training and testing split), we will use similar data in both train and test sets resulting in a problem of overfitting during validation.

Feature Selection

Feature selection is the process of selecting a subset of the most relevant features that are linked to the injury prediction output. This technique reduces the dimensions of the feature space, making the machine learning models easier to interpret and faster to train, with a lower risk of multi co-linearity issues. For example, Rossi et al. [15] selected the best features with reference to injury forecasting by using a *Recursive Feature Elimination with Cross-validation (RFECV)* process. The aim of RFE is to select features by recursively considering smaller and smaller sets of features. Feature selection should be performed on the training set in order to check for eventual overfitting issues during model goodness assessment.

Hyper-Parameters Fit on Validation Set

In the validation set, is it possible to fit the best machine learning hyper-parameters to improve the injuries prediction performances. Hyper-parameter tuning represents a paramount key process, as they control the overall behaviour of a machine learning model. Every machine learning model has different hyper-parameters that can be set. One traditional and common way to perform hyper-parameter tuning is termed Grid Search while another approach to detecting the best hyper-parameters is the Random Search.

Model Interpretation

Machine learning models are becoming increasingly complex, powerful, and able to make accurate predictions. However, as these models become "black boxes," it is even harder to understand how they arrived at those predictions. This has led to a growing focus on machine learning interpretability and explainability. Accordingly, model interpretation represents a challenging step that allows practitioners to modify the training schedule reducing the risk of injury maximizing the effect of training. process. For example, Pappalardo et al. [75] proposed a method to explain their convolutional neural network model by using the *SHAP (Shapley Additive exPlanations)* method.

SHAP uses game theory to explain the output of any machine learning model. SHAP values, measure how much each feature (such as external load, internal load, wellness, recovery) contributes to the model's prediction. SHAP values can help you see which features are most important for the model and how they affect the outcome.

Prediction Goodness

The reliability of a machine learning model is a key measurement for assessing the model's capacity to identify connections and patterns among variables within a data set, based on its training data. An ML model's ability to extend its application to 'unseen' data enables it to generate more predictions and insights, thus augmenting its market worth.

Confusion matrix, also called error matrix, is a specific contingency table (with two dimensions, i.e., “actual” and “predicted”), that allows for the visualization of the performance of an algorithm). In this table, each row represents the instances in a predicted class, while each column represents the instances in an actual class (i.e., injury [true positive (TP) and False Negative (FN)] and not injury [false positive (FP) and True Negative (TN)]).

Several metrics are derived from the confusion matrix in order to evaluate machine learning classifiers goodness:

- Precision (Sensitivity) is the ratio between the true positive (TP) and all the positive results, i.e., the sum of the true positive and the false positive (FP): $TP/(TP + FP)$. The positive class in this example is the injury one. Precision indicates the fraction of examples that the classifier correctly classifies in a given class over the number of all examples the classifier assigns to that class.
- Recall (Specificity) is the ratio between TP and the number of all samples that should have been identified as positive, i.e., the sum of TP and False Negative (FN): $TP/(TP + FN)$. The recall an index that indicates the number of examples that a classifier correctly classified in a given class.
- F1-score = $2(\text{precision} \times \text{recall})/(\text{precision} + \text{recall})$. This is the harmonic mean of Sensitivity (precision) and Specificity (recall).
- Area Under the Curve (AUC) is an aggregate measure of performance across all possible classification thresholds. In particular, it is the probability that a model ranks a random

positive instance is higher than a randomly negative one. The AUC score is ranged between 0.5 and 1. The higher the AUC, the higher the accuracy of the model.

Worth noting, to assessing the injury prediction models' goodness considering the performance of the classifiers as the metrics mean of the two classes should not take into consideration as that the dataset is extremely unbalanced, resulting in an average value strongly affect by no-injury class. Accordingly, assessing the metric values in both the classes allows for a better understanding of the model goodness. In particular, the injury class metric values provide the ability of the machine learning models for injury prediction.

A review carried out by Leckey et al. (138), have reviewed the current state of machine learning research for the prediction of sports-related injuries. Authors reported that XGBoost and Random Forest showed the highest-performing methods, XGBoost was the only method found to provide the highest statistical performance in each of the studies in which it was applied. As AUC was the most commonly reported metric of model evaluation (71% of studies), it provides the most effective means of performance comparison between reviewed studies. Worth noting, authors have identified several ML techniques and highlighted the large variation in predictive model performance in the included studies. This variability could be due to inconsistencies in many aspects of the study design, such as data collection methods, study populations, definition and scope of injury, sources of data and dependent variables analysed. Indeed, football studies included in this review reported seven different ML approaches as providing the best predictive performance, emphasising the individuality of each dataset and the need to select the appropriate ML method for the type of data being analysed.

To delve into the knowledge of implication of Machine learning on injury forecasting, we direct readers to Rossi review. In the chapter III we will delve into the application of Machine Learning in soccer.

1.1. Training load and injuries prediction: a machine learning approach

Given a large amount of data available due to training/match monitoring, the forthcoming need to translate this data into helpful knowledge and practical solutions have involved informatics and the engineering industry (139). To date, artificial intelligence (AI) techniques and methods are growing fast to provide sophisticated analysis to investigate the complex phenomena associations and prediction such as training load, injury and performance in soccer. In this way, Claudino et al., 2019 have reviewed the application of AI for injury risk assessment and performance prediction in team

sport (140). Authors reported that for injury risk assessment, the artificial neural network, decision tree classifier, and support vector machine had been frequently used in soccer and other team sports. Also, the use of machine learning could have great potential to unearth new insights into the workload and injury relationship (141). A great contribution in this area has been provided by the review on machine learning application in soccer carried out by Rico-González et al., 2022 (142). Authors have clustered all articles into three groups: injury, performance (which was classified in match/league outcomes forecasting, physical/physiological forecasting, and technical/tactical forecasting) and talent forecasting (142). Concerning injury prediction, this study found that the best attempts at predicting injury incidences are derived from pre-season screening, training load, genetics, or risk factor surveys (personal, psychological, and neuromuscular). Moreover, injuries can be predicted through algorithms such as decision trees can with an accuracy greater than 66%. Specifically, pre-season anthropometrics (height, weight, and sitting height), physical fitness (strength, flexibility, speed, agility, and endurance) screening (143) as well as training load (distance covered at different intensities (total distance, high-speed running (HSR) and explosive distance), metabolic load related features, accelerations/decelerations, dynamic stress, and fatigue index (106) should be considered as input variables associated with injuries prediction. In detail, Rossi et al., 2018 (106), have proposed a multi-dimensional injury forecaster in a real-world injury prevention scenario (13). Authors found that the decision tree technique can detect around 80% of the injuries with about 50% precision “far better than the baselines and state-of-the-art injury risk estimation techniques”. The decision tree trained in the study of Rossi et al. has provided a small rate of both false positive and false negative. In terms of injury prevention, 60% of the injuries occurred long after a previous injury with specific values of high-speed running distance (Exponential Weighted Moving Average, i.e., decreases the weights of the values exponentially according to their recency) and total distance (based on monotony calculation, i.e., the ratio between the mean and the standard deviation of the values of the feature in the last week), which indicate that the player's kinematic variability is related to his injury risk (106). Authors suggest that care should be taken when players who recently returned to play after an injury perform the total distance and the distance at high-speed running. It is worth noting that a single feature alone does not provide significant predictive power, while a combination of the three features allows for predicting injury.

A detailed analysis of machine learning approaches and their implication on injury prediction will be provide in chapter III.

Chapter II – Understanding soccer Physical Performance and Training Load

2.0 Overview

In the last ten year, studies have investigated the training load and physical performance implications on soccer context. Despite theoretical information have been published, literature lack to a consensus on training load monitoring, providing evidence in deeply understanding of external load behaviour during different kind of sports specific drills and official match as well as providing practical insight in the real word context related to the differences between physical performance and training load. In particular, through a conceptual framework we will delve into the construct of training load highlighting the differences between volume and intensity. Moreover, the intensity concept in soccer has never been clearly defined, leading to lack of consensus about the meaning and its relative indicators to assess it as well as misconceptions, and misunderstanding about it. Intensity can be considered as a key performance “target” to reach during soccer performance including both training and competition. Indeed, practitioners seek to planning training considering both running and soccer-specific drills aiming to adapt players to withstand the high intensity efforts required by official match. Moreover, over the last thirty years the physical demands in terms of performance such as high-speed running, acceleration, power output in short actions both with and without the ball have increased significantly. This justifies the great interest in intensity both among practitioners and the scientific community. Accordingly, this section will offer an overview on intensity concept in soccer through a conceptual framework. At the end of this section, we will also provide an overview in which both theoretical aspects and practical proposals on training prescription based on player monitoring in a real soccer scenario will be presented.

List of publications/projects discussed within Chapter II:

Guglielmo Pillitteri, Filipe M. Clemente, Marco Petrucci, Alessio Rossi, Marianna Bellafore, Antonino Bianco, Antonio Palma, and Giuseppe Battaglia -

Toward a New Conceptual Approach to “Intensity” in Soccer Player’s Monitoring: A Narrative Review (2023) - The Journal of Strength and Conditioning Research – doi:10.1519/JSC.0000000000004503

Guglielmo Pillitteri, Filipe Manuel Clemente, Hugo Sarmento, Antonio Figueiredo, Alessio Rossi, Tindaro Bongiovanni, Giuseppe Puleo, Marco Petrucci, Giuseppe Battaglia -

Translating player monitoring into training prescriptions: Real world soccer scenario and practical proposals - International Journal of Sports Science & Coaching – doi: 10.1177/1747954124128908

2.1 Toward a New Conceptual Approach to “Intensity” in Soccer Player’s Monitoring: A Narrative Review

Pillitteri G., Clemente FM, Petrucci M, Rossi A, Bellafore M, Bianco A, Palma A, Battaglia G. (2023). Toward a New Conceptual Approach to "Intensity" in Soccer Player's Monitoring: A Narrative Review. J Strength Cond Res. 2023 Sep 1;37(9):1896-1911.

INTRODUCTION

Soccer performance is characterized by repeated high-intensity intermittent effort that involves both metabolic (i.e., aerobic and anaerobic) and neuromuscular components (61). On average during a match, elite soccer players run for 9-14 km covering 22–24% of the total distance faster than 15 km/h (high-intensity), 8–9% faster than 20 km/h (very high-intensity), and 2–3% faster than 25 km/h (sprinting threshold) (144, 145). Most recent approaches used to analyse soccer performance propose to include the energetic cost of accelerations to improve the estimation of the metabolic power (146). In particular, these approaches provide higher estimation of the “high-intensity activities” compared to the values obtained from traditional video match analysis. It is worth noting that a 2% increase in total distance covered and a 30% increase in high-intensity runs between the 2006/2007 and 2012/ 2013 seasons has been reported. This result clearly indicate that soccer games are continuously increasing and becoming more physically demanding (144). It is also worth noticing that physical demand is highly related to players’ playing positions. It is because every playing position have specific technical-tactical requests that are also strictly related to different physical, physiological, energetic, and biomechanical components (147-149). For example, previous studies reported that wide midfielders and fullbacks reached the longest distance covered at high intensity (150, 151). Moreover, wide players (full-backs and wide midfielders) and central midfielders usually perform more high-intensity distance compared to attackers and central backs

(144, 152), while attackers and wide players usually perform more sprint compared to other playing positions (153). However, the high-speed activity performed by a player vary within a single match and between matches (75). Specifically, very high between-match variations were observed at the end of the matches induced by a reductions in high speed running (HSR) performance (75). However, previous studies suggested that personalization of HSR thresholds according to fitness characteristics might provide more stable indicators of running performance and fatigue occurrence reducing also the between- and within-match variability (75).

Monitoring the Training Load (TL) represent a relevant practice during training process aiming to control the players' demands, enhance performance and possibly reduce injury risk in young (19) and adult soccer players. Indeed, literature indicates that inappropriate load management is related to a significant increase of risk factor for acute illness and overtraining syndrome (154). For example, it was found that high loads could affect the injury risk in athletes. Moreover, large fluctuation in TL is not recommended because athletes respond better to training stimuli when small variation in TL are scheduled (155). Actually, there are evidence from several sports that if load is employed in a moderate and progressive approach avoiding rapid fluctuations (i.e., increases or decreases) could be protective against non-contact injuries (155). In recent years, technological evolution allows to easily monitor players performance permitting to create large data set that warrants to have a complete overview of the players' status (139). In this way, a huge quantity of tools and indicators are now developed in order to evaluate loads in elite professional soccer (139). Actually, experts have highlighted that to date no single measure can accurately quantify the fitness and fatigue responses to training stimuli, but they encourage the use of both external and internal load index as information that describe training-load adaptation (156).

Training Load , in the framework of sport training, has been defined “as a higher-order construct reflecting the amount of physical training that is actually done and experienced by the athletes” (17). In general, it is scheduled in order to induce the desired training responses that are supposed to be related to performance (4, 157). Two sub-dimensions called internal (IL) and external (training) load (EL) (4, 158) characterized the TL. Commonly, training prescription refers only to the EL (4, 157) and in particular to total distance, range of speed covered, accelerations, and metabolic power (146). EL stimuli induces internal responses on psychological, physiological, biochemical, metabolic, and biomechanical domains (21, 38, 57, 158, 159). In order to enhance performance and possibly reduce injury risk, practitioners have to schedule TL in accordance with match demands (21, 22, 38, 160). Despite Staunton et al., reported a scientific incorrect use of “load” terminology (161), Impellizzeri et al., 2022, confirms its appropriateness encouraging the use of this terms by

practitioners (162). TL have been defined as the input variable that is usually manipulated to reach training or match outcomes (24, 30, 56, 163). Impellizzeri et al (2018) explained the fundamental training notion of stimulus-response dose concept introducing both internal and external load domains (30). Based on this framework, the total amount of mechanical and locomotive stress generated by athletes during exercise (e.g., total or high intensity distance running travelled, time spent in speed or accelerations zone, and number of intense accelerations or decelerations) has been usually referred to external TL. Meanwhile, the subjective and individual physiological and psychological (e.g., rating of perceived exertion [RPE], HR, blood lactate) response to the external TL imposed on the athlete has been considered as internal one (21, 30). However, authors considered TL as the amount of stress placed on an individual in response to an exercise over a period of time (21). In fact, TL has been calculated as the product of volume and intensity of an exercise (i.e., training impulse) (164). Some authors have considered session RPE (i.e., product between RPE and exercises duration; S-RPE) as a measure of TL (164, 165), while others used both intensity and volume related indicators to assess TL. Indeed, Casamichana et al. 2013, calculated external load considering both running distances (i.e., volume) and frequency of efforts at high running speeds (i.e., intensity) (20). Hence, there seems to be confusion regarding the right way to monitor TL because of the huge quantity of “load” (both intensity and volume related) indicators nowadays recordable (22, 62, 64, 78). In light of this, practitioners should understand the meaning of “intensity”. The term intensity in physics has been defined by the Oxford English Dictionary as “A measurable amount of energy, brightness, magnetic field, etc..” Consequently, this term can be applied to the physical exercise (166). The suitability of ‘intensity’ to express the effort of exercise was first promoted by Knuttgen et al., 1978 (167) and later again by Winter et al., 2015 (166). The term intensity describes “how hard someone is exercising” and can be apply to all forms of static and dynamic exercise allowing the categorization of exercise into domains (e.g., moderate, heavy, very heavy, severe, and extreme) that are based on physiological responses (166, 168).

Despite the huge interest from sports and exercise scientists, ‘intensity’ has never been universally defined in sport science literature due to the several different components involved in soccer performance. Indeed, it might be inappropriate referring to soccer intensity using only internal or external indicators or considering only one of them. Conversely, the physical demand for track and field endurance athletes is well characterized, allowing practitioners to focus on specific intensity indicators. Actually, intensity criteria for endurance athlete has been selected based on %VO₂ max, % HR max, lactate concentrations and self-report of training pace based on questionnaire and

anchoring with different running paces (e.g., below-marathon pace, 10 K pace, 3 K pace) coherently with physical demands (i.e., cyclic running activity involving aerobic metabolism prevalently) (169).

Based on these considerations about intensity, several questions raised. What is meant by intensity in soccer? What are the indicators to consider? Can practitioners evaluate the intensity considering a single approach or a single indicator? To answer at these questions, the main aim of this narrative review is to report the different intensity criteria used in literature to assess physical performance and TL in soccer. Moreover, we try to understand if it is possible to consider only one intensity approach (i.e., external or internal) or if a single indicator can fully describe intensity even if soccer physical performance is complex and multifactorial. Finally, a new conceptualization to well establish the meaning of intensity will be reported.

1. MEANING OF INTENSITY: ABSOLUTE VS RELATIVE AND INTERNAL VS EXTERNAL APPROACHES

Physical activity exercises induce individuals' functional adaptive responses that elicit changes in various training outcomes such as physical performance and injury resistance (30). The athlete's response to the stimulus and the stimulus itself are related to the nature, intensity, and duration of the exercise (170). TL represent the input variable that field experts could manipulate to obtain the required training outcomes (163). Previous studies recommended first considering the internal TL due to its direct effect on the training outcome (athlete adaptations). In fact, specific athlete-related factors such as training status and genetic characteristics can lead to an individual internal response for a similar external load. (24, 30, 171). Anyhow, nowadays, coaches train athletes to reach the highest level of performances based on external TL.

During a soccer match, athletes performed 150-250 different actions, 1100 changes of direction, and the typology of physical activity performed by each player changes every 4-6 seconds (53). Due to the complexity of the soccer match-demand, evaluating both internal and external load provide a holistic overview of the TL (20, 22, 90, 172) due to the fact that two athletes carrying out the same external load could result in different internal load and consequently in different training adaptation (30, 173). In soccer, the duration of the training task is usually considered as volume while training intensity has been described through several indicators (both internal and external). In sport, intensity defines the magnitude of the activity that is correlated with the athlete response. Indeed, the exercise

intensity is referred to the level of muscular activity quantifiable in terms of power, force or velocity (161, 166).

Exercise intensity can be defined in absolute and relative terms and measured in internal (i.e., physiological) or external (i.e., locomotor and mechanical) components (161). For example, in running, speed of movement ($\text{m}\cdot\text{s}^{-1}$) has been considered as an absolute external exercise intensity indicator, while power (W), acceleration ($\text{m}\cdot\text{s}^{-2}$) and force (N) reflect absolute external exercise intensity in cycling or rowing (161). Regarding absolute internal exercise intensity, physiological responses such as oxygen consumption (VO_2) expressed in litres per minute ($\text{L}\cdot\text{min}^{-1}$) or HR (beats per minute ($\text{b}\cdot\text{min}^{-1}$)) has been evaluated (174, 175). Additionally, differently from absolute values, relative ones provide normalized score - both external (e.g., percentage of maximal speed or power) and internal (e.g., RPE and percentages of HRmax or $\text{VO}_{2\text{max}}$) load - in accordance with sport's demand (21, 30, 161, 162). Although studies carried out in soccer employed absolute external or internal intensity approaches (21, 90, 176), we speculate that should be necessary consider both *relative* external and internal factors to correctly evaluate the exercises' intensity in soccer. Actually, an athlete can perform a large quantity of high intensity running, but with a low internal response (e.g., low percentage of HR max). Hence, which component (internal or external) explain better the concept of intensity? Moreover, values provided by absolute internal or external intensity indicator cannot explain if an activity is intense for an athlete since being measurable, it presupposes a relationship with another measure. This makes it even more complex since relationships between internal and external load are not linear and depends on the outcomes considered (22). In order to better explain this concept, we report two examples in the next sections implementing a new "conceptual framework". A previous study have assessed the distance run at high-intensity during matches through individualized high-intensity speed threshold based on the speed at the second ventilatory threshold (VT2speed) (56). These authors found that the high intensity running speeds based on an objective and individualized method are lower than the ones computed by using the "default" match analysis system thresholds (56). Therefore, the use of standardized threshold (both internal or external) is not enough to explain if an exercise or training session can be considered intense or not. This study showed that players present different speed at which they begin to run at high-intensity highlighting the fact that it is required to individualize the high-intensity speed threshold in accordance to individual players' characteristics (56).

Previous studies have reported several conceptual issues considering both internal and external intensity indicators in soccer. For example, literature found that S-RPE and HR derived measures were more associated with volume (i.e., Total Distance, Low Running Intensity) than intensity (175,

177). Moreover, it was also found that this correlation is lower when intensity thresholds increase (175, 177). Indeed, Scott et al. (2013) reported that cardiac response is more associated with distance covered at low speeds than the one covered at high speeds (178, 179). Thus, HR and RPE underestimate the internal response due to the fact that anaerobic metabolism is primarily involved during short high-intensity activities (178, 179) that characterizes the intermittent nature of soccer game (85, 178). Consequently, RPE could be underestimated in specific-ball tasks because it seems to be more related to non-specific metabolic activities in which HR show a linear response (85, 178). Moreover, concerning external intensity, evaluating intermittent activity only by using speed measures permits to assess only a partial component of external physical demand (70). Indeed, studies reported that Player Load (calculated from accelerations) is largely associated with S-RPE (85, 176, 178). Moreover, Gaudino et al. (2015) stated that for assessing performance demands, the use of metabolic power (derived by speed and accelerations) is more appropriated respect to the use of only speeds (85). Hence, for monitoring training in soccer, the use of both categories of external load (i.e., speed and acceleration) is found to be better related with S-RPE compared to the use of only one of them alone (85, 180).

2. INSIDE ON HIGH INTENSITY TRAINING (HIT)

a. HIT: FROM PHYSIOLOGY TO TRAINING PERIODIZATION

In the last decade, several studies have been focused on high intensity interval training (HIT) as the most efficient method for enhancing physical performance (181). Bucheit & Laursen (2013) have deeply reviewed both the physiological and practical application factors underlying the HIT “world” (8, 33). This approach is characterized by repeated short-to-long bouts of high intensity exercise separated by recovery periods (33, 182, 183). HIT protocols is found to be the most effective stimulus to stress oxygen transportation permitting to reach a very high percentage of VO₂max (184). Consequently, exercise intensity near to VO₂max allows to recruit type II muscle fibre (185) that permits to achieve near-to-maximal cardiac output and consequently permits to increase muscular and cardiac adaptations. However, previous studies suggested that HIT exercises should be performed for at least ten minutes at intensity greater than 90% of VO₂max to obtain an optimal adaptation stimulus (i.e., cardiovascular, and peripheral) (181-183). In addition, HIT training session should engage both metabolic (e.g., VO₂, cardiovascular work, stored energy and cardiac autonomic stress responses) and neuromuscular systems (i.e., anaerobic glycolytic energy contribution and neuromuscular load/musculoskeletal strain) to obtain the optimal training stimulus (8, 33, 186).

The physiological response to an HIT session depends on different factors such as training specificity (sport which athlete is involved) and athlete's profile. For example, different from a marathon runner, a 100m runner requires anaerobic-based HIT exercises during training program. Moreover, for team sports athletes that have to training both metabolic and neuromuscular system concurrently, the physiological impact should be modulated in relation to the physical and technical-tactical demands related to competitive season commitments in order to improve performance during match day and reduce the overall injury risk (187). Bucheit & Laursen (2013) reported that at several variables could be manipulated to propose different HIT sessions that produce different effect on metabolic, cardiopulmonary and neuromuscular responses (33). These variables include the intensity and duration of the work, the relief intervals, the number of series, and the between-series recovery time. Noteworthy, Bucheit's review reported that HIT exercises performed at the second ventilatory threshold or maximal lactate steady state are useful to improve VO₂max in running training and in soccer players during specific tasks such as SSG (33).

b. HIT FOR TRACK AND FIELD VS TEAM SPORTS ATHLETES

In order to prescribe an appropriate HIT format where those athletes achieve the required intensity, the individualization of the exercise speed and power (e.g., through field test) is required. It is well known that a huge difference exists between team sport and track and field athlete training approach (8, 22, 33, 169). Actually, specific running speeds based on set times for different target distances (e.g., 800 m or 5000 m) are used to plan HIT for endurance runners. For example, for HIT exercise with short intervals (i.e., 10–60 s) the reference running time was set as the percentage of the time needed to cover 100–400 m sprint at maximal speed (33). However, this approach did not consider the individual physiological response affecting individual physiological adaptations, but it is focused only to reach the best athlete's performance. Differently, team sport performance is characterized by technical / tactical demands and, for this reason, it is necessary to look for specific adaptations during training (SAID principle) (188). About that, specific tasks as Small Sided Games (SSG), considered as specific HIT format (8), have been largely proposed to enhance soccer performance (189, 190). Furthermore, through SSG physical, tactical, psychological, and technical components can be elicited at the same time (190) although these tasks do not completely reproduce the real “external” demands of the game (191).

During matches (both official and friendly) players performed higher maximal peak speeds and very high average speed than SSG (191). Consequently, practitioners should include in the training process

more generic HIT format (e.g., run based) to achieve the desired stimulus useful that permits to simulate the player's performance (33). Moreover, within-player responses to SSG are highly variable (poor reliability for blood lactate and high-intensity running responses), and the between-player variability in the cardiovascular responses is higher compared to more specific run-based HIT (190). It worth noting that although HR has been considered the mainly physiological marker to assess intensity in the field (192), its usefulness for detect the intensity of an HIT session may be limited. Indeed, HR cannot inform the intensity of physical work performed above a specific speed/power threshold associated with VO₂max (33). It has also been observed a temporal dissociation between HR, VO₂, lactate levels and work output in both run-based HIT and SSG (193). Hence, the use of HR alone is not appropriate to understand intensity during HIT sessions. Also, RPE methods has been used to establish intensity in HIT sessions despite this approach could provide insufficient and incomplete information in team sports due to the fact that it may be dependent on age, fitness, exercise-intensity, pleasure and exercise typology (33, 105, 164). Other methods used to determine intensity in HIT refer to the speed (or power) associated with VO₂max (i.e., v/p VO₂max or maximal aerobic speed/power [MAS/MAP]) (182). v/p VO₂max is the lowest speed/power needed to elicit VO₂max and represents the athletes' locomotor ability (182). The use of this index as "gold standard" running speed intensity is appropriate for long intervals (2–6 min) that are ran around vVO₂max (90–105 %). Thus, other variables (e.g., blood lactate concentrations) must be included for prescribing supramaximal (i.e., above vVO₂max) training in order to elicit anaerobic components (8). In order to determine performance during shorts all-out efforts, practitioners should consider Anaerobic Speed Reserve (ASR, calculated as the differences between Maximal Sprinting Speed (MMS) and vVO₂) (33, 194). Notwithstanding, these variables cannot be enough when planning specific HIT session (i.e., repeated-sprint sequences (RSS) and SSG) for intermittent sports like soccer. Indeed, the physiological response during HIT characterized by repeated very short work intervals (i.e., <45 s) seems related to VO₂ kinetic at the onset of each short interval, physiological recovery capacities during each relief interval, and change of direction ability (33). Actually, Bucheit (2013) suggests using the 30–15 Intermittent Fitness Test (30–15IFT) developed for intermittent exercise and change of direction (COD) to appropriately prescribe HIT training sections. (37) This test permits to reach maximal HR and maximal VO₂ where the final speed (i.e., VIFT) refers to ASR, repeated effort ability, acceleration, deceleration, and COD abilities measures. This approach allows intensity individualization of the prescribed interval bouts around intensities ranging from 85 % to 105 % of VIFT (33, 195). However, practitioners do not need to individualize the exercise intensity for HIT protocol due to the fact that it involves all-out running such as short (3–10 s, repeated sprint training, RST) or long (30–45 s sprints, sprint interval training, SIT) sprints (33). Finally, long-bout HIT has

been proposed to endurance-trained athletes while team sports players usually perform short-interval HIT, RSS and game-based training (e.g., SSG).

c. HIT IN SOCCER: GENERAL VS SPECIFIC TRAINING

Different HIT formats have been proposed to enhance athletes' performance based on their own physical demand (8, 33). We highlighted the huge training difference between endurance and team sports athletes in previous section. Actually, in soccer, several training methods have been implemented. In particular, they include both general and specific exercises that are proposed in accordance with the periodization principle (196). Considering general HIT, it seems possible calibrate exercise intensity focusing on specific external and internal indicators with good accuracy. Indeed, as mentioned above, during HIT the intensity of the speed running has been found to be related to the physiological variables (e.g., $\dot{V}O_2$). Specifically, based also on intensity criteria, HIT can be classified as repeated short (< 45 s) to long (2–4 min) bouts performed with rather high- but sub maximal-intensity, or short (i.e., ≤ 10 s, RSS) or long (> 20 –30 s, sprint interval training, SIT) of all-out sprints, and relative recovery periods (8). Among HIT format, game-based training (e.g., SSG) represent an important training modality to improve soccer performance (190, 197). Nevertheless, establish the intensity of this HIT is not simply. Actually, a “gold standard” has never been stated because its response is highly variable within- and between- players (8, 54). In soccer, short-bouts HIT (e.g., 15s-15s with 85 % of $\dot{V}O_{2max}$ interspersed by passive recovery) is used to perform exercise at a high intensity with a relatively low production of blood lactate (8, 69). In this way, practitioners can modulate the work interval intensity and duration of short HIT exercises - relief interval intensity and duration – with the aim of modulating anaerobic contribution (8). Moreover, high contribution of anaerobic glycolytic energy has been observed during RSS. Indeed, previous studies reported that sprints longer than 4 s (i.e., 25 m with recovery interval less than 20 s and generally active) induce an high initial rate of blood lactate accumulation (i.e., >10 mmol/L/5 min) (8). It worth noting that along with metabolic responses, neuromuscular contribution during HIT exercise should be considered due to large implication in performance development and injury risk. For example, it has been observed that short HIT format requiring more accelerations, decelerations that induce high neuromuscular load. Indeed, quadriceps and hip adductor are elicited during “small” soccer specific tasks while hamstring muscle are stimulated by high-speed running performed in larger spaces (8, 198). Furthermore, the presence of change of directions contributes to increase neuromuscular effort. To date, the possibilities of directly measuring the neuromuscular response (i.e.,

internal intensity) during soccer specific tasks performance is not possible. Only through GPS or inertial accelerometer it is possible to detect this response related to neuromuscular load such as accelerations, decelerations and direction change indicators (172, 193).

3. EXTERNAL APPROACH FOR DETERMINING THE INTENSITY IN SOCCER

Several studies have evaluated the training workload in soccer measuring the external intensity through the most common microelectromechanical (MEMS) systems (e.g., global positioning system, local positioning system, inertial measurement units) (38, 78) and in particular through numerous metabolic and mechanical indicators (23, 105). Usually, intensity was measured by several EL indicators related to time (e.g., distance per minute, number and distance of accelerations and decelerations per minute, high-speed running distance/time per minute) (78). Table 2 presents the main external intensity indicators commonly used to assess soccer performance.

During the planning phase, the intensity of both general and specific activities is sought by coaches. The intensity of general activities (e.g., intermittent exercise or HIT execution protocols) can be established by determining relative speed through several individual tests. For example, Yo-Yo Intermittent Recovery Level 1 (58) and 30–15 Intermittent Fitness Test (30–15IFT) (199) have been used to determine the reference speed useful for planning metabolic workouts (e.g., short-format HIT). On the other hand, it is not possible to determine the intensity by considering during specific activities (e.g., SSG) a-priori (i.e., in the planning phase). Indeed, practitioners can detect external intensity only after performing these exercises typology. Consequently, only using video match analysis or MEMS systems it is possible assess tasks intensity.

In this perspective, the first relevant studies carried out in soccer employed external indicators considering only speed parameters (49, 55, 145, 153). Specifically, various speed thresholds have been implemented to classify intense activities as shown in Table 2. Actually, the results of these studies indicated that, on average, players spend 70% of the total match duration performing low-intensity activities such as fast walking and jogging, whereas they are involved for at least 30% of the time in high-intensity exercise. Moreover, “sprinting” activity (running speed above a lower limit ranging from 19 to 25,2 km·h⁻¹) has been observed on 5%–10% of the total distance covered during a match (i.e., 1%– 3% of the match time). Surprising if compared to the average speed maintained by elite marathoners (i.e., 20 km/h) (200). It is worth noting that the exclusive application of “speed approach” underestimates the concept of intensity in soccer. In fact, Osgnach et al (2009) have

revolutionized the concept of intensity in soccer proposing a new approach based on energy contribution of accelerations (70). The authors considered metabolic power (Watt), defined as the product of the energetic cost of acceleration running ($EC, J \cdot kg^{-1} \cdot m^{-1}$), and speed ($v, m \cdot s^{-1}$), as intensity indicators (70). Contributions of accelerations characterize the physical performance in soccer. Hence, the acceleration should be taken into account for appropriately monitoring performance of athletes. Moreover, since roles have specific technical-tactical requests strictly related to different physical, physiological, energetic and biomechanical components it was found that soccer physical demand is extremely related to players' positions on the pitch (148, 201).

4. INTERNAL APPROACH FOR DETERMINING THE INTENSITY IN SOCCER

External training stimuli determine the internal athlete responses (30). The internal training physiological response is characterized by a complex and multifactorial construct that make its direct assessment difficult when using a single indicator (202). RPE, blood lactate concentrations %HR represent the main intensity indicators that have been included in soccer analysis of performance. Table 2 shows the main internal indicators considered in soccer. Studies that carried out on soccer performance are focused only on physiological aspect through field and laboratory test (174) (145, 153). However, this approach did not consider relevant aspects of performance such as activities that determine the athletes' internal responses (e.g., distance, speed).

Despite the huge use of HR, RPE and derived session-RPE (s-RPE) in soccer studies, some limits of using these variables for assessing the internal load have been highlighted. For example, S-RPE is more associated with volume indicators (e.g., total distance, Low Running Intensity) than intensity ones (85, 178). Specifically, the correlations were lower considering higher intensity thresholds and when speed was increased (e.g., High-Speed Running and Very High-Speed Running distance, High Intensity Events $>2.5 m \cdot s^{-1}$, and High Intensity Events $>3.5 m \cdot s^{-1}$ (85, 160, 176, 177, 179). S-RPE and EL intensity features are poorly related in intermittent exercise due to other psychobiological factors that could influenced the individual's perceived exertion (22). Indeed, main multidirectional and unpredictable soccer's activity such as acceleration, deceleration, and change of direction as well as technical activity are performed at low speed although involves a high amount of muscular contraction (22). Similarly, the unclear relationship between S-RPE and EL intensity measurements can be explained by a different training modality used in soccer (22). Other authors shows that RPE can be underestimated during intermittent exercise (85). However, to monitor different trainings activities, a combination of EL indicators should be implemented as more related to S-RPE when

compared to one parameter approach (85, 203). Considering HR, Scott et al. (2013) reported that cardiac response is more associated with distance covered at low speeds than higher ones (178, 179) due to the anaerobic metabolism role during these activities. Indeed, during short high-intensity intermittent activities that required a high rate of anaerobic metabolism, HR can be underestimated (178, 179). Also, RPE could be underestimated in specific-soccer tasks (e.g., SSG), and it seems to be more related to non-specific metabolic activities (e.g., running) in which HR has a linear response (85, 179).

Borg studied the relationship between HR and RPE reporting the increased of this common scale with the magnitude of HR increase during cycle ergometer exercise (204). American College of Sports Medicine have recommended the use of RPE to monitor exercise intensity (205, 206) because its strong correlated with specific intensity indicators (e.g., threshold intensity expressed by HR, VO₂, or blood lactate measures) (174). Indeed, Losnegard et al. highlighted the strong relationship between RPE and %HR, %VO₂, and blood lactates during submaximal and maximal tests (running or cycling) (207). However, these relevant correlations have been found through linear running laboratory and field test (174). Accordingly, it has been speculated that RPE could not be highly appropriate to assess internal intensity in soccer, even if even it represents the most used tool by practitioners (85, 164, 175). S-RPE could be poorly appropriate to assess TL because both RPE and duration seems to be not an appropriate intensity indicator in soccer. However, to date it is not yet possible to determine fundamental components of performance such as the real energy expenditure related to cognitive, technical, emotional, and neuromuscular demands due to the lack of an appropriate technological tool.

Table 2. Main Soccer Internal and External intensity indicators			
Studies Author, year	Measures of load		Findings
	Internal Intensity indicators	External Intensity indicators	
Mhor, 2003		Standing (0 km*h ⁻¹), walking (6 km*h ⁻¹), jogging (8 km*h ⁻¹), low-speed running (12 km*h ⁻¹), moderate-speed running (15 km*h ⁻¹), high-speed running (18 km*h ⁻¹), sprinting (30 km*h ⁻¹) and backward running (10 km*h ⁻¹).	The results of this study show that top-class players performed more high-intensity running during a game and were better at the Yo-Yo intermittent recovery test than professional players at a less elite standard. In addition, the players' physical performance was reduced after a period with a large amount of high-intensity exercise during match-play and towards the end of the match. These effects were observed independent of position played in the team. It was also clear that the physical performance and activities of elite players are closely related to the positional role in the team;

Impellizzeri, 2006	Training-Heart Rate (HR) data were expressed as percent of HRmax and classified into five intensity zones: < 80%, 80–85%, 85–90%, 90–95%, and > 95%	Standing (0 km·h ⁻¹), walking (including backward and side-ways, 5.2 km·h ⁻¹), jogging (including low-intensity, sideways and backwards running, 7.6 km·h ⁻¹), low-speed running (10.2 km·h ⁻¹), moderate-speed running (13.9 km·h ⁻¹), high-speed running (17.1 km·h ⁻¹), running sprint (26.7 km·h ⁻¹), sprints below 2 s (17.8 km·h ⁻¹), sprints above 2 s (25.1 km·h ⁻¹).	small-sided games can be used as an effective training mode to enhance aerobic fitness and match performance in soccer players. Because no differences were found between specific and generic aerobic interval training, the choice of the aerobic training mode should be based mainly on practical necessity.
Rampinini, 2007		The time spent in six locomotor categories (standing [from 0 to 0.7 km·h ⁻¹], walking [from 0.7 to 7.2 km·h ⁻¹], jogging [7.2 to 14.4 km·h ⁻¹], running [from 14.4 to 19.8 km·h ⁻¹], high-speed running [from 19.8 to 25.2 km·h ⁻¹], and sprinting [> 25.2 km·h ⁻¹]). 1) total distance covered (TD); 2) high-intensity running distance (running speed > 14.4 km·h ⁻¹ , HIR); 3) very high-intensity running distance (running speed > 19.8 km·h ⁻¹ , VHIR). 1) VHIR distance with the ball (VHIRWB) and without the ball (VHIRWOB); 2) frequency of HIR and VHIR; 3) the highest speed recorded during the game for each player (peak speed).	Top-level soccer team's physical performance during a match performance is re-lated to the activity completed by the opponent team and the competitive level of that team. In addition, the present results demonstrate for the first time, that the decrement in physical performance during the second half is related to the activity completed during the first half, and that both the player's match activity profile and their interaction with the ball is related to their playing position.
Di Salvo, 2008		Total high intensity running (THIR) distance (average running speed > 19.8 km / h over a 0.5 s time interval); Total sprint distance (TSD) (average running speed > 25.2 km / h over a 0.5 s time interval). Total high intensity running was also expressed as both total HIR distance completed with the respective players team in possession (HIRP) and without (HIRWP) possession of the ball. Further analysis of sprint activity (> 25.2 km / h) included the total number of sprints and the number of 0 – 5 m, 5.1 – 10 m, 10.1 – 15 m, 15.1 – 20 m and > 20 m sprints completed. The type of sprint activity (Explosive and Leading) ^a was also analysed.	The data illustrated that THIR is not only affected by playing position but is also linked to the success of the team. The ability to perform these intense efforts seems to be reduced across the duration of the match, especially in those positions requiring players to perform frequent intense actions. Seasonal variations in sprinting were also observed across three competitive seasons indicating that the requirement to produce intense efforts varies with time.
Osgnach, 2009		The following six speed categories were used: walking (from 0 to 8 km·h ⁻¹), jogging (from 8 to 13 km·h ⁻¹), low-speed running (LSR; from 13 to 16 km·h ⁻¹), intermediate-speed running (ISR; from 16 to 19 km·h ⁻¹), high-speed running (HSR; from 19 to 22 km·h ⁻¹), and max speed running (MSR; <22 km·h ⁻¹), max deceleration (MD; <-3 m·s ⁻²), high deceleration (HD; from -3 to -2 m·s ⁻²), intermediate deceleration (ID; from -2 to -1 m·s ⁻²), low deceleration (LD; from -1 to 0 m·s ⁻²), low acceleration (LA; from 0 to 1 m·s ⁻²), intermediate acceleration (IA; from 1 to 2 m·s ⁻²), high acceleration (HA; from 2 to 3 m·s ⁻²), and max acceleration (MA; <3 m·s ⁻² low power (LP; from 0 to 10 W·kg ⁻¹), intermediate power (IP; from 10 to 20 W·kg ⁻¹), high power (HP; from 20 to 35 W·kg ⁻¹), elevated power (EP; from 35 to 55 W·kg ⁻¹), and max power (MP; <55 W·kg ⁻¹).	The main aim of this study was to propose a new approach in the analysis of soccer player performance taking into account also the phases of accelerated and decelerated running, which constitute a large and crucial fraction of every match.
Bradley, 2010		Player activities were coded into the following categories and speed thresholds: standing (0–0.6 km/h ⁻¹), walking (0.7–7.1 km/h ⁻¹), jogging (7.2–14.3 km/h ⁻¹), running (14.4–19.7 km/h ⁻¹), high-speed running (19.8–25.1 km/h ⁻¹), and sprinting (<25.2 km/h ⁻¹). High-intensity running consisted of running, high-speed running, and sprinting (<14.4 km/h ⁻¹). Very high-intensity running consisted of high-speed running and sprinting (≥19.8 km/h ⁻¹). Players' accelerations were divided into 2 subsets: medium (2.5–4.0 m/s ²) and high (>4.0 m/s ²).	The physical load placed on elite players is high and that the high-intensity profile, mean recovery time, and maximal running speed are similar between performance levels, over the course of the game, but vary markedly between playing positions. These data provide valuable information to the fitness coach about the high-intensity activity profile of elite soccer players at different performance levels and playing positions.

Orendurff, 2010		Seven categories were established based on the step rate data (≥ 6 = sprinting, 5 = cruising, 4 = running, 3 = jogging, 2 = walking, 1 = shuffling, and 0 = standing) ^b .	The distribution of sprinting, cruising, running, jogging, walking, shuffling, and standing in this study is similar to other work investigating the distribution of running intensity during soccer matches. All studies of workload intensity during matches demonstrate the tendency for soccer players to have less activity at the extreme ends of the spectrum and more activity near the moderate to moderately high intensity levels.
Mendez-Villanueva, 2012	HR1, < 60 % HR max; HR2, 61–70 % HR max; HR3, 71–80 % HR max; HR4, 81–90 % HR max; HR5, > 91 % HR max	Speed zone 1 (S1): below 60 % of MAS ^c , speed zone 2 (S2): from 61 % to 80 % of MAS, speed zone 3 (S3): from 81 % to 100 % of MAS, speed zone 4 (S4): from 101 % of MAS to 30 % of ASR ^d and, speed zone 5 (S5): above 31 % of ASR. Using these relative speed zones, total distance (i.e., S1 + S2 + S3 + S4 + S5), distance run at intensities below MAS (i.e., S1 + S2 + S3) and distance run at intensities above MAS (i.e., S4 + S5) were calculated	1) younger players exercised at higher relatively running intensities than older players; 2) the substantially different relative running demands for each playing position were not influenced by a player's physical capacity; 3) despite the marked differences in relative running demands for the different age groups and playing positions, there were no differences in HR responses between age groups and playing positions; 4) average relative running speeds were not different between age groups and playing positions at HR intensities above 80 % of HR max; 5) a superior aerobic fitness level was unlikely to affect total distance covered but was associated with a reduced individual running demand; 6) in the second half, the reduction of total distance covered was explained by covering significant less distance below MAS, irrespective of the playing position, while distances covered above MAS were maintained; 7) the reduction in total distance covered below MAS in the second half was not related to a player's physical capacity.
Aslan, 2012	Blood Lactate (LA), HR and rate of perceived exertion (RPE). The field test was administered in order to determine the players' fixed blood lactate concentrations (FBLs) and maximal oxygen consumption (VO2max) values.	(a) walking (W; 0 to 6.0 km·h ⁻¹), (b) jogging (J; 6.1 to 8 km·h ⁻¹), (c) low intensity running (LIR; 8.1 to 12 km·h ⁻¹), (d) moderate intensity running (MIR; 12.1 to 15 km·h ⁻¹), (e) high intensity running (HIR; 15.1 to 18 km·h ⁻¹), (f) low intensity sprint (LIS; 18.1 to 21 km·h ⁻¹), (g) moderate intensity sprint (MIS; 21.1 to 24 km·h ⁻¹), (h) high intensity sprint (HIS; above 24 km·h ⁻¹) and (i) total distance (TD).	Based on LA, HR and RPE responses, the present findings indicated that young soccer players experienced a higher physiological stress during the 1st half of the matches compared to the 2nd half. Even though the 2nd half of the matches was lower in terms of the volume and intensity of running compared to the 1st half, RPE values gradually increased throughout the matches. In addition, although, the movement patterns of players differed greatly across playing positions, the distances covered at FBLs were similar, except for average running speed a 2mmol·L ⁻¹ (FBL2). Therefore, it can be concluded that the external load imposed on players differed in accordance with position played in the field, but that all players experienced a similar physiological stress during the matches, as supported by HR and RPE responses to match play.
Buchheit, 2013		MAS; Maximal sprinting speed (MSS); High-speed efforts were defined as at least 1-s runs > 19 km·h ⁻¹ repeated high-speed sequences (RHSS) and RSS were defined as a minimum of 2 consecutive ≥ 1 -s high-speed efforts (RHSS) or sprints (RSS) interspersed with a maximum of 60 s of recovery.	1) a substantial increase in either MSS or velocity (V Vam-Eval ^e) was at least likely associated with a greater RHSS occurrence, while the magnitude of this increase was position-dependent, 2) a substantial increase in either MSS or V Vam-Eval was likely associated with a lower RSS occurrence during games, but for some playing positions only, 3) despite the limited available data, substantial reductions in either MSS or V Vam-Eval were associated with maintained or even small-to-moderate increases in the occurrence of both RHSS and RSS, and finally 4) the effects of substantial changes in physical capacities on the number of high-speed efforts and sprints per RHSS and RSS were clearly position-dependent.

Bradley, 2013		Walking (<7.1 km* ^h ⁻¹), jogging (7.2–14.3 km* ^h ⁻¹), running (14.4–19.7 km* ^h ⁻¹), high-speed running (19.8–25.1 km* ^h ⁻¹) and sprinting (>25.1 km h ⁻¹). The speeds for each category have been employed previously Total distance represented the summation of distances in all categories. High-intensity running consisted of the combined distance in high-speed running and sprinting (≥19.8 km* ^h ⁻¹) and was separated into three subsets depending on the teams' possession status (with/without ball) or if the ball was out of play.	(1) less total and high-intensity running distance was covered in the Premier League compared to lower standards in English soccer, (2) players covered more high-intensity running when moving down from the Premier League to the Championship but not when moving up standards, (3) technical indicators in the Premier League were superior to lower standards and (4) physical capacity did not differ between a subsample of players in each standard but correlated with high intensity running performed in the competition.
Casamichana, 2015	(%HRmean) and RPE	TD, total distance covered (m·min ⁻¹); b) DHS, distance covered at high speed without limit (>18 km·h ⁻¹), in m·min ⁻¹ ; (c) DSS, distance covered at sprint speed without limit (>21 km·h ⁻¹), in m·min ⁻¹ ; (d) FHS, frequency of effort at high speed without limit (>18 km·h ⁻¹); and (e) FSS, frequency of effort at sprint speed without limit (>21 km·h ⁻¹) in n·min ⁻¹ . Player load (PL)	In training programmes of this kind it is necessary to consider a range of intensity indicators so as to obtain complementarily information and enable coaches to assess more accurately the load imposed on players. This is because in the majority of cases there is only a low or moderate correlation between various external load indicators, as well as between these and the internal load indicators.
Aasgaard, 2018	The highest recorded HR value was considered as HRpeak and used for subsequent reporting of relative HR intensities (%HRpeak). The average and maximum HR, and time spent ≥90% HRpeak for the duration were also determined. RPE was measured on a 1–10 category ratio (CR) scale.	Workload (m*min), total distance (TD) covered, and maximum and average speed (speed peak and speed average, respectively), as well as distance covered (DC) in the following speed bands: 0–6.9 km>h ⁻¹ (walking), 7–13 km>h ⁻¹ (jogging), 13.1–17.8 km>h ⁻¹ (striding), 17.9–21 km>h ⁻¹ (high-intensity running [HIR]), and <21 km>h ⁻¹ (sprinting)	Man-marking (MM) during soccer-specific SSGs invokes a greater perceptual load, as well as increase DC at velocities greater than 13.1 km* ^h ⁻¹ . Players spend less time walking (0.9–3.4%) during MM, while Speed ave, distance covered striding and HIR, is increased during MM SSG irrespective of player number. Conversely, a greater metabolic demand was identified with lower player numbers, likely due to increased accelerations and decelerations with less recovery opportunities, which are reflected in the greater RPE scores reported by players.
Abbott, 2018		Maximum sprint speed (MSS), and MAS to determine anaerobic and aerobic locomotor capabilities respectively. Anaerobic speed reserve (ASR). Speed-related GPS metrics recorded were maximal speed achieved, very high-speed running distance, and sprinting distance. Very-high speed running, and sprinting distances were characterised as the distances travelled between 100% MAS – 30% ASR, and >30% ASR respectively. Acceleration-related GPS metrics recorded were moderate-intensity (MI) acceleration, and high-intensity (HI) acceleration distances. These were characterised as distances travelled accelerating between 50-75% and >75% of an individual's maximal accelerative capacity respectively. The total distance travelled during competition was also recorded.	The current investigation demonstrates the significant differences in physical demands elicited upon soccer playing positions during competition. In addition to differing tactical and technical roles, each playing position has a specific physical demand associated. Findings provide coaches with the information to accurately prescribe training intensities above those encountered during competition. Further individualisation can be achieved by prescribing training intensities to specific playing positions.
Zurutuza, 2020	Each zone has a value associated with it (50–60% HRmax = 1, 60–70% HRmax = 2, 70–80% HRmax = 3, 80–90% HRmax = 4, and 90–100% HRmax = 5); time spent at more than 80% of the maximal HR (T > 80%HRmin)	Peak velocity (Vmax), total distance (DTmin), distance covered at less than 60% (D < 60%min), between 60 and 80% (D > 60%min) and more than 80% (D > 80%min) of the maximal velocity of each player, player load (PLmin), and distance covered accelerating at more than 2 m*s ⁻² (Dacc > 2min) and decelerating at less than -2 m*s ⁻² (Ddec < -2min).	(1) through PCA ⁹ analysis, determine the minimum amount of variables necessary to obtain the essential information and (2) thus obviate redundant information in workload analysis and help to save effort on the part of physical trainers and increase the quality of their analyses.
Modric, 2021		Both official matches (RMs) and training demands (RTs) included the total distance covered (m), low-intensity running (<14.3 km/h), running (14.4–19.7 km/h), high-intensity running (>19.8 km/h), high-speed running (19.8–25.1 km/h), sprinting (>25.2 km/h), number (frequency) of total accelerations (>0.5 m/s ²), number of high-intensity accelerations (>3 m/s ²); number of total decelerations (less than -0.5 m/s ²), and number of high-intensity decelerations (less than -3 m/s ²). Relative Training Load (RTL) was assessed by Training match ratio (TMr), by dividing the training demands (i.e., RTs) by	First, RTL (assessed by TMr) were the highest on MD-3 and the lowest on MD-1 and MD-2. Second, accelerations, decelerations, total, and low-intensity distance covered during training were, in general, closest to the corresponding match values, indicating that the observed players were undertrained in high-intensity running during in-season training sessions. Third, the identified associations between match outcome and all TMr indicate an important influence of RTL on success in soccer

the match demands (i.e., RMs) based on the following formula: $TMr = RT/RM$.		
Rhodes, 2021	Accelerations $>3 \text{ m/s}^2$ and decelerations $<3 \text{ m/s}^2$	There were very large differences observed between the frequency of high-intensity accelerations and decelerations regardless of match performance outcome (i.e., win, draw, lost).
Teixeira, 2021	The sRPE was obtained by multiplying total duration of training sessions for each individual RPE score ($sRPE = RPE * \text{session duration}$) following a scale from 6 to 20	HMLD ^b (m), sprinting (SPR) distance (m), dynamic stress load (DSL) (a.u.), number of accelerations (ACC) and number of decelerations (DEC). The GPS software provided information only about the locomotor categories above $19.8 \text{ km}\cdot\text{h}^{-1}$: rHSR ⁱ ($19.8\text{--}25.1 \text{ km}\cdot\text{h}^{-1}$) and SPR ($>25.1 \text{ km}\cdot\text{h}^{-1}$). Both acceleration variables (ACC/DEC) considered the movements made in the maximum intensity zone ($>3 \text{ m}\cdot\text{s}^{-2}$ and $<3 \text{ m}\cdot\text{s}^{-2}$, respectively).

a: An explosive sprint (characterised by a rapid acceleration) was defined as the attainment of sprint speed ($> 25.2 \text{ km/h}$) from either standing, walking ($< 7.2 \text{ km/h}$), jogging ($< 14.4 \text{ km/h}$) or running ($< 19.8 \text{ km/h}$) with time spent in the high speed run category (From 19.8 to 25.2 km/h) less than 0.5 s . A leading sprint (characterized by a gradual acceleration) was defined as the attainment of sprint speed from either standing, walking, jogging or running whilst entering the high-speed run category for a minimum of 0.5 s . b: Data were further analyzed using custom code written in MATLAB (The Mathworks, Natick, MA). This code was designed to quantify each period with step rates ≥ 4 as a work bout and each period, < 4 as a recovery bout. For each subject and each bout, 4 values were calculated: bout duration; mean step rate, maximum step rate, and minimum step rate. Step count data were collected during a soccer match using StepWatch Activity Monitors (SAM; OrthoCare Innovations, Mountlake Terrace, WA). StepWatch Activity Monitors count an acceleration that occurs once during the gait cycle (usually foot contact or foot off) and then lock out for a time equivalent to cycle time. c: MAS, maximal aerobic speed; d: anaerobic speed reserve. e: A modified version of the University of Montreal Track Test (UMTT) (i.e., Vam-Eval) was used to estimate MAS. The Vam-Eval is very similar to the UM-TT, i.e., same speed increments. f: Anaerobic speed reserve (ASR) was calculated (difference between the MSS and MAS score and reported in $\text{m}\cdot\text{s}^{-1}$). g: Principal Component Analysis. h: high metabolic load distance. The HMLD is a metabolic variable defined as the distance, expressed in meters, covered by a player when the metabolic power exceeds $25.5 \text{ W}\cdot\text{kg}^{-1}$. HMLD variables include all high-speed running, accelerations and decelerations above 3 ms^{-2} i: relative high-speed running

5. IS THERE AN INTEGRATED APPROACH TO DETERMINE SOCCER INTENSITY?

The use of both external and internal indicators to monitoring training soccer was carried out by several studies. In these works researchers have stated that the use of one indicator approach alone (i.e., external, or internal) could not permit to fully evaluate the athlete's training effects (17, 30). This is because it would not be possible to understand the athlete's fitness or fatigue condition (i.e., training effect). For example, considering similar training programme (e.g., 1000m running in 4 minutes), athletes that present low internal response (e.g., HR) show higher *fitness status* (i.e., athlete's physical performance). Therefore, considering a single indicator approach for training evaluation do not allow to fully understand both the training session or exercise and the athlete intensity. Nowadays, recent studies try to create new indexes for combining Internal Load (IL) and External Load (EL) (86, 172, 197, 208, 209) as shown in Table 2.1-2.2. Grünbichler et al. (2020) set up a workload index (Effindex) calculated as the ratio between equivalent distance (i.e., external load) and TRIMP_{mod} (modified training impulse that describes time spent in certain HR zones multiplied by a weighting factor) (86). The main advantage of this approach is that this index was influenced by total and sprinting distance. Interesting, author found that the training loads recorded during the days before a match can predict

match workload efficiency. Differently, Suarez-Arrones et al. (2015) (209) and Torreño et al. (2016) (172) used another performance (Effindex) to quantify the match stimuli dose-response. This index is calculated as the ration between mean speed (in $\text{m}\cdot\text{min}^{-1}$) and mean exercise intensity (%HRmax). Effindex was found in players with highest overall running performance levels during matches. Moreover, Suarez-Arrones et al. (2015) showed several statistically significant differences among playing positions considering both physical and physiological demands of professional soccer players. Similarly, Torreño et al. (2016) found difference between pitch roles reporting that midfielders performed the highest while central back the lowest physical and physiological demands.

Derbidge et al. (2020) proposed three new different ratios: Total Distance/HRe (HRe represents the total volume of cardiovascular exertion an individual will experience relative to time), Player Load/HRe, and Equivalent Distance/HRe (197). Authors revealed a significant effect of EL/IL ratios on subjective fatigue, while a non-significant effect for neuromuscular fatigue. Moreover, Malone et al. (2018) used EL/IL ratios that was found to be correlated with both high-speed and maximal running speed (208). The authors revealed significant effects of wellbeing on both external and integrated training load measures. Reinhardt et al. (2020) compared the Effindex (used previously by Suarez-Arrones (209)) and a new performance index (PI – product between Effindex and the number of acceleration (210). This study found that PI is more suited to distinguishing between player's performance as might be more related to exhaustion. Indeed, recent studies claiming that quantifying the in-game acceleration and deceleration profiles is more sensitive to fatigue than the distance at predefined locomotor category. Thus, PI seems to be a useful parameter to enhance the quality of match analysis allowing a better planning and monitoring soccer-specific physical training. Indeed, a massive metabolic load occurs during the intense phases of the match (intended as high running speed) and whenever the acceleration is high even when the speed is low (68, 70) confirming the fundamental role of accelerations on soccer performance. Furthermore, two studies from Akubat et al. (2014) used a ratio between iTRIMP (Individualized Training Impulse and HR parameter related to blood lactate) and EL indicators in non-professional soccer (83, 90). In these studies, authors underlined the relevant implication of the use of this ratio in evaluating the state of fitness compared with the use of a performance indicator alone (i.e., external load). Moreover, one study carried out by Montini et al. showed a positive correlation of energy expenditure (EE) ($\text{kJ}\cdot\text{kg}^{-1}$) and S-RPE (211) against of these indexes.

The indexes or ratios provided in this section allow assessing the soccer players physical performance. In particular, the integrated approach (using both EL and IL) explains the individual internal response to a given EL (i.e., athlete fitness status) which would not be possible to achieve

using a single parameter alone. In the next sections will be provide a conceptual framework (i.e., a process in which imprecise constructs and their constituent components are defined in precise terms) to better understand the “intensity” in the soccer context.

Table 2.1 Main Characteristics of studies that used internal/external load ratio or index

Studies Author, year	Sample number / level / age (years) / mass (kg) / height (cm)	Duration	Obs. Sample Obs. per athlete/tot. individual obs.	Findings
Akubat, 2014	10/ amateur soccer players/20 ± 1, 69.87 ± 8.32/179 ± 8	2-week		TD:iTRIMP and HID:iTRIMP showed large correlations with velocity at lactate threshold (vLT) and velocity at onset of blood lactate accumulation (vOBLA), respectively, showing that the integration of both the internal and external load is potentially more useful than using external TL alone
Akubat, 2018	10/ amateur soccer players/20 ± 1, 69.87 ± 8.32/179 ± 8	2-week		In rested conditions, all of the external:internal training load ratios show large relationships with measures of fitness.
Grunbichler , 2020	14/Austrian Second League/ 22.6 ± 4.3/181.5 ± 5.7/ 75.7 ± 5.8	13-week period (competi tive season) 2017/20 18 from March 2018 until June 2018	514 individuals training and 180 match observations/4 4 training sessions and 16 competitive matches	Training loads recorded during the days before a match can predict match workload efficiency.
Lacome, 2018	10/elite French football team/26±5/76±5/1 82±6	one season (2016/2 017)		Large associations between the heart rate (HR) responses to Small Side Games (SSGs) and some SSGs assessed with GPS. HRA can be used.
Malone, 2018	48/(Liga NOS and Champions league)/25.3 ± 3.1/183 ± 7/72 ± 7	2014/20 15 season	22080 individual pitch-based training sessions / 460 training sessions	The current study supported the utility of wellbeing measures. Wellbeing measures were related with reduction in training measures.
Montini, 2020	20/Italian (Serie A) 25.8 ± 4.1/76.8 ± 4.3/184 ± 4.6	October 2016 to August 2017	In-season period (34 training sessions and matches (October 2016 and December 2016); the pre- season (30 training sessions and matches (July and August 2017)	S-RPE and kJ as the most effective training load indicators in soccer.

Reinhardt, 2020	Fifty-five sub-elite soccer players (German 3rd and 4th league)/24.6 ± 3.7/79.3 ± 6.5/182.5 ± 6.3	three successive seasons (2016/17 2018/19)	485 matches	In general, running performance was lower in comparison to elite players. Positional differences and performance decreases in the 2nd half were observed. PI is much more variable within the position groups. Thus, this parameter is more suited to distinguishing between player's performance.
Suarez-Arrones, 2015	30/Champions League or UEFA Europa League	two seasons	(n = 348)/ 4-15 times on each player over a period of two seasons	Physical and physiological demands of professional soccer players assessed with GPS and HR response showed several statistically significant differences between the different playing positions.
Torreno, 2016	26/national league, national cup, national super cup and UEFA Europa League/27.3 ± 3.4/180.4 ± 3.6/76.2 ± 6.8	two seasons	(n = 223 match files)/ 3-15 times on each player over a period of two seasons	Decrement in players performance toward the end of game in all playing positions. It also confirmed that midfielders (W-MD) performed the highest physical and physiological demands. Central back (CB) performed the lowest physical and physiological demands. The relationship between external and internal load measures among position-specific confirms that players with more overall running performance during the full-match (W-MD and 2ndS) presented the higher values in Effindex.
Derbidge, 2020	10/professional development league/19.6 ± 1.4/74.4 ± 8.7/180.5 ± 5.3	2018/2019 8-week period during the in-season competitive phase	7 training sessions	The significant effect observed between perceived wellness and TD: HR exertion (HRe), PL: HRe and equivalent distance (ED): HRe during the SSG's allow scope for external:internal (E:I) ratio's to be used as a 'invisible' fatigue detection tool. E:I ratios is not an appropriate method to determine neuromuscular fatigue.

Table 2.2 Internal and external Device/parameters and Relationship/index External/internal load ratio of studies

Studies Author, year	Measures of load		Relationship/index External/internal load ratio
	Internal Device/parameters	External Device/parameters	
Akubat, 2014	HR was recorded using HR belts (Polar Team System, Polar Electro, OY, Finland). Mean HR during the last minute of each stage was used in the calculation of the individualized HR–blood lactate relationship for the calculation of iTRIMP ^a weightings.	5-Hz GPS system (Minimax, Catapult Innovations, Australia). Total distance (TD) and high-intensity distance (HID) using a threshold of 15 km/h.	TD:iTRIMP and HID:iTRIMP ratios
Akubat, 2018	HR was recorded using HR belts (Polar Team System, Polar Electro, OY, Finland). Mean HR during the last minute of each stage was used in the calculation of the individualized HR–blood lactate relationship for the calculation of iTRIMP ^a weightings.	5-Hz GPS system (Minimax, Catapult Innovations, Australia). PlayerLoad™. It also provided data for accelerations and velocity which was used in the calculation of mean metabolic power (MMP) and distance covered at high metabolic power (HP; >20 W·kg ⁻¹).	TD:iTRIMP; HID:iTRIMP; PL:iTRIMP; MMP:iTRIMP; HP:iTRIMP

Grubichler, 2020	Polar Team Pro System (Polar Electro Oy, Kempele, Finland). 200 Hz movement sensors as well as heart rate sensors duration (min), Polar Modified training impulse (TRIMPMOD)	Polar Team Pro System (Polar Electro Oy, Kempele, Finland) 10 Hz global positioning (GPS) Duration (min), total distance (m), equivalent distance (m), high speed running (> 14.4 km/h) dist. (m), very high speed (> 19.8 km/h) running dist. (m), sprinting (> 25.2 km/h) dist. (m), number of medium (2.00 – 2.99 m/s ²) and high (> 3.0 m/s ²) acc. number of medium (-2.00 – -2.99 m/s ²) and high (< -3.0 m/s ²) dec.	new index= workload efficiency (ratio of external and internal load in a match); ED/TRIMPMOD
Lacome, 2018	Heart rate: Polar H1 units (Polar, Kempele, Finland)	5-Hz GPS and 100 Hz accelerometers (SPI-Pro, Team AMS R1 2016.8, GPSport, Canberra, Australia) Total distance (TD, m), high-speed distance (HS, above 14.4 km.h-1, m), very-high speed distance (VHS, above 19.8 km.h-1, m), velocity and force load (vL and fL respectively, a.u) mechanical work (MechW, a.u)	HRA (i.e, the difference between the predicted and actual HR)
Malone, 2018	Borg CR-10 rate of perceived exertion (RPE) scale. RPE was multiplied by the session duration to generate an RPE-load	Global positioning technology device, with tri-axial accelerometers (MinimaxX, Team 2.5, Catapult Innovations, Australia). Tot. dist. (m), Tot. high-speed dist. (≥19.8 – 25.2 km·h-1), sprint dist. (≥ 25.2 km·h-1), max vel. (km·h-1), max vel. Dist. (m), max vel. exposures (n), player load (AU), player load slow (AU)	Total Distance:RPE (m·min-1) Total High Speed Distance:RPE (m·min-1) Player Load:RPE (AU·min-1) PlayerLoadslow:RPE (AU·min-1)
Montini, 2020	RPE: CR-10 scale Session rating of perceived exertion values was obtained by multiplying the value of the 10-point Borg scale and the training duration in minutes	GPS device (20 Hz GPS system; GPEXE, Exelio Srl, Udine, Italy) operating at a sampling frequency of 18.18 Hz. Total energy expenditure was expressed in kJ·kg21. Such parameter represents the total external training load	Individual index between ITL and ETL parameters.
Reinhardt, 2020	HR time series were filtered with a moving-average filter with a span of 10 s (using the MATLAB function <i>smooth</i>) to avoid artifact peaks. From the filtered time series, the physiological demands were estimated as average HR (ØHR), separately for the whole match time and both halves.	GPS-based tracking system (Polar Team Pro, Polar Electro, Kempele, Finland) that combines signals from a 10 Hz GPS with a 200 Hz microelectromechanical inertial measurement unit consisting of a tri-axial accelerometer, gyroscope and magnetometer. The following locomotor category were analyzed: standing (STA, [0.0–0.7 km/h]), walking (WAL, [0.7–7.2 km/h]), jogging (JOG, [7.2–14.4 km/h]), running (RUN, [14.4–19.8 km/h]), high-speed running (HSR, [19.8–25.2 km/h]), and sprinting (SPR, [> 25.2 km/h]). HSR and SPR were additionally summarized to very high-intensity running distance (VHIR).	Efficiency index (EI) Performance index (PI). In both methods of calculation, the running pace of the players (v, in m/min) is divided by ØHR. This term is additionally multiplied by n° of acceleration (related to the minutes of play) in the case of PI.
Suarez-Arrones, 2015	Short--range telemetry (SPI-Pro--X, GPSports, Australia) (HRmax)	GPS unit (SPI Pro X; GPSports Systems, Canberra, Australia)5 Hz and accelerometer data at 100 Hz respectively N° of Sprints, Average time of sprint (s), Average minutes between sprint, Average Sprint Distance, Maximal Sprint Distance, Maximal Speed, RSS (Repeated-Sprint Sequence), Relative total distance (RD) (m·min--1) ^b , Work--to--rest ratio (RD>7.0 km·h--1/ RD≤7.0 km·h--1)	The performance efficiency (Effindex) ^c
Torreno, 2016	HR: HR belts (Polar®, Finland) The data stored includes HR, time, speed, and distance.	GPS unit (SPI Pro X; GPSports Systems, Canberra, Australia) GPS 5 Hz frequency and accelerometer data to 100 Hz Tot. dist. covered (TD), distance covered running above moderate-speed (>13.0 km·h-1), above high-speed (>18.0 km·h-1).	The performance efficiency (Effindex)
Derbidge, 2020	HR monitors (T31, Polar, Finland) A novel measure of HR exertion (HRe) ^d HR max	10Hz GPS unit integrated with a 100 Hz accelerometer (Viperpod, Statsports, Ireland) TD (m), PlayerLoadTM(PL) (au) and Explosive distance (ED) (is the cumulative distance an individual has spent accelerating and decelerating >2 m/s) (m)	E:I Ratio (au) = external load/internal load TD: HRe, PL: HRe ED: HRe

a: method, which determines TL by calculating the product of the accumulated training duration (minutes) in 5 HR zones applying a coefficient relative to each zone (50 – 60% of HRmax = 1; 60 – 70% of HRmax = 2; 70 – 80% of HRmax = 3; 80 – 90% of HRmax = 4; 90 – 100% of HRmax = 5) and then summing the result. b: RD: 0.1 -- 7.0 km·h--1 (m·min--1), RD: 7.1 -- 13.0 km·h--1 (m·min--1), RD:13.1 -- 18.0 km·h--1 (m·min--1), RD:18.1 -- 21.0 km·h--1 (m·min--1), RD: >21.0 km·h--1 (m·min--1), RD: >13 km·h--1 (m·min--1), RD: >18 km·h--1 (m·min--1); c: was calculated as [mean speed in m·min--1/mean exercise intensity (%HRmax)]; d: HRe represents the total volume of cardiovascular exertion an individual will experience relative to time;

6. CONCEPTUALISATION AND OPERATIONALIZATION OF INTENSITY FRAMEWORK: WOULD IT BE POSSIBLE TO CONSIDER ONLY ONE INTENSITY INDICATOR APPROACH?

Intensity describes “how hard an exercise is” or “how heavy a stimulus was for an athlete (i.e., how hard the training session was or will be).” However, in order to affirm that a physical task is intense, it has to be compared (through indicators measurement) (166) with the quantity of “energy” consumed during another task. In fact, a training session could be more intense for an athlete when compared to the other players, but it could be less intense if compared with their previous session. As a matter of fact, in our conceptual framework, intensity should be seen as a *relative concept* because of the individual athlete responses (i.e., through physiological internal intensity indicators) or the result of training (i.e., external intensity). While based on previous considerations, athlete's physical performance can be assessed implementing both internal and external indicators (i.e., EL/IL ratio).

Actually, it would not be appropriate to talk about intensity without considering the exercises' time or distance (i.e., volume) and without relating it to a reference measure. For example, an internal intensity indicator does not provide the training effect (i.e., how hard someone is exercising) unless the volume that produced that external response is considered.

In this way, %HR, %VO₂max or RPE have been commonly used to monitor soccer performance (38, 64, 78). However, it seems impossible to detect “how long a session was” without considering the training exposure time (i.e., volume). In this perspective, the concept of intensity is strictly related to both TL (calculated as the product between intensity and training duration) and performance (calculated as amount of work carried out in the unit of time such as distance/minute or accelerations/minute). Intensity derives from a multidimensional construct (212) that comprise two sub dimensional element, i.e. internal and external factors, for which a single operational measure cannot explain all the meaning of intensity in soccer (30). Several variables (or indicators) are required to evaluate athletes training (and soccer tasks) and can be operationalised following different approaches (i.e., internal and/or external). In this perspective, practitioners should not confuse the meaning of an intensity indicator (e.g., speed above 25 km/h) that can only explain if an activity/action may be considered as "intense" compared to another activity (e.g., speed between 0-8 km/h). Conversely, “intensity” refers to "how intense a session is" for an athlete or “how intense a task/training is.” Indicators are important tools that just allow assessing component of performance and cannot explain the “intensity concept.”

Furthermore, as defined by the Oxford English Dictionary, the “measurable quantity of something,” e.g., energy or training results, is linked to concept of relationship and / or comparison. Thus, the absolute intensity cannot be included in our intensity conceptualisation framework (161). For example, considering the training 1 as reported in Table 2.3, which training is more intense? Considering external indicators, athlete A performed the exercise with higher “intensity” activity compared to athlete B (i.e., has performed 1000 m running faster than athlete B). Otherwise, referring to internal indicators such as HR and RPE, athlete B trained more intensely (i.e., has performed 1000 m with a higher percentage of HR than the athlete B). Hence, consider only one intensity indicator approach permits to partially evaluate the players’ physical performance. This example highlighted that is necessary consider both external and internal indicators to compare the “intensity” differences between two athletes answering the question "which athlete trained more intensely? Accordingly, we can assert that there is a widely evaluative difference when considering the external or internal intensity whereby each one provides fundamental and indispensable aspects to understand the effects of training.

We hence proposed a more complex approach to evaluate a task intensity in soccer specific training (i.e., SSG). If two 2, athletes perform the same SSG assuming the same internal response (considering RPE or %HR), when speed indicator was considered, athlete B showed higher TL (i.e., 1500 a.u.), while based on metabolic power indicator, athlete A presented the highest TL, as shown in Table 2.4. Through this simple example we can recognize that practitioners should implement more indicators to fully evaluate the “intensity” concept related to task/training or athlete performance. It would be impossible to understand the exercise intensity without relating the result given by an external indicator (e.g., 200m distance at 19.98 speed) to the "time" factor. Moreover, by relating the internal response of an athlete with speed, distance, and power (i.e., external activities) is it possible to define the concept of athlete performance (referring to the internal responses of the athlete). Most importantly, each indicator provides a partial information about performance, and, for this reason, practitioners should combine several external intensity indicators to have a holistic assessment of the soccer physical performance. In this way, our framework suggests that, in order to evaluate the intensity of a given exercise or the intensity related to athlete match/training, it would be appropriate to consider both approaches (internal and external) including all the indicators necessary to explain soccer physical performance (e.g., speed and metabolic power). Actually, Osgnach et al (2009) has revolutionized the concept of intensity in soccer through the new approach based on energy contribution of accelerations reporting that the speed indicators have underestimated the soccer intensity. The authors considered metabolic power (70) to more appropriately monitor tasks and

athlete performance. Finally, athlete physical performance could be defined as “the relative internal effort recorded by the player based on the activity produced in training or competition.” Intensity is defined as “the result of the performance provided by a measurable and comparable amount of work relative to the time, operationalized through factors external and internal to the athlete (Figure 2).”

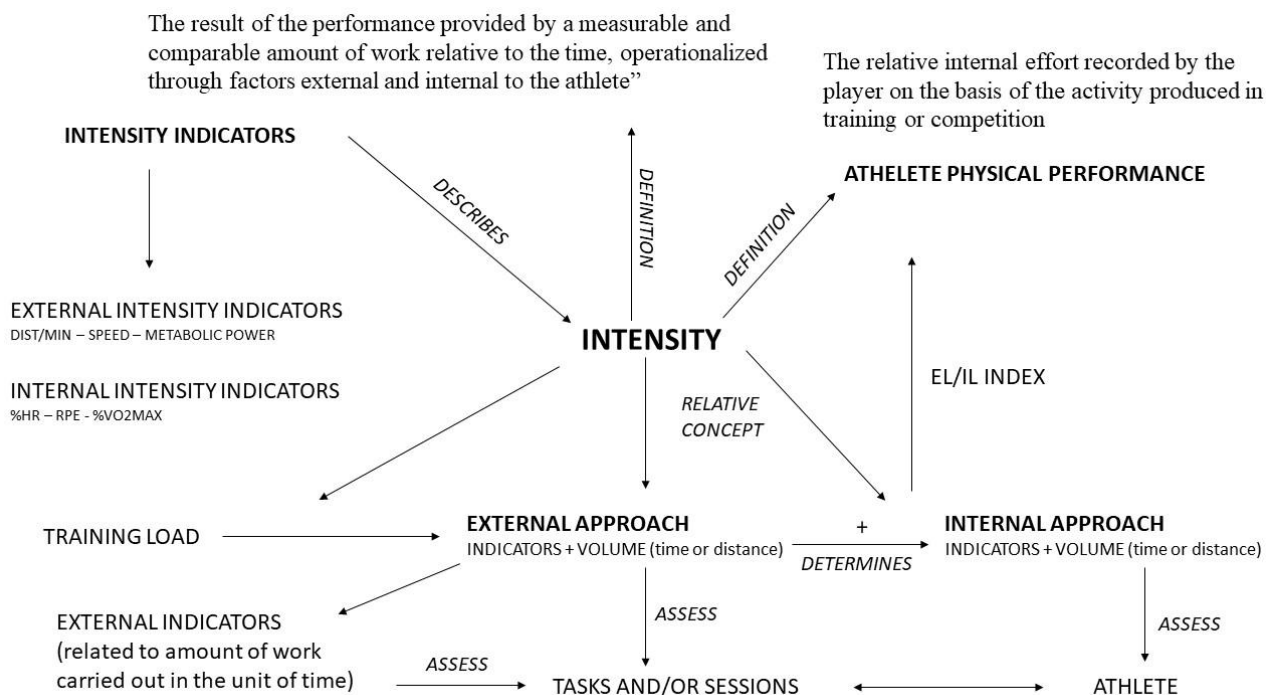


Figure 2 – Intensity conceptual framework

Intensity is operationalized through external and internal indicators. Intensity represents a relative concept that allows to assess (1) tasks and/or training sessions and (2) athlete responses given the amount of work related to time.

Athlete physical performance can be defined as the athlete responses to a given external activity (i.e., fitness status). It can be operationalized by EL/IL ratio. Considering only one intensity approach (i.e., external, or internal) cannot explain intensity concept. To understand “intensity” related to prestatative model is necessary includes different indicators such as speed, accelerations, and metabolic power.

Table 2.3, example of calculation of different training load on general aerobic running				
	ATHLETE A		ATHLETE B	
TRAINING 1 Objective: general aerobic running	Exercise: 1 x 1000m running		Exercise: 1 x 1000m running	
	External indicators	Internal indicators	External indicators	Internal indicators
	Time: 3 min Speed: 19,98 Km/h	%HR max= 80 RPE: 6	Time: 4 min Speed: 14,7 Km/h	%HR max= 90 RPE: 9
	TRAINING LOAD: Based on internal indicator 3x6=21 u.a.		TRAINING LOAD: Based on internal indicator 4x9=36 u.a.	

	ATHLETE PHYSICAL PERFORMANCE INDEX 3/6*100= 50	ATHLETE PHYSICAL PERFORMANCE INDEX: 4/9*100= 44

Table 2.4, example of calculation of different training load on soccer specific aerobic task (i.e., Small Sided Games)				
	ATHLETE A		ATHLETE B	
TRAINING 2 Objective: soccer specific aerobic task (SSG)	Exercise: 1 x 5' SSG (5 vs 5+2Gk, 40x35m, 140 m ² /player)		Exercise: 1 x 5' SSG (5 vs 5+2Gk, 40x35m, 140 m ² /player)	
	External indicators Distance Speed > 19 Km/h: 200m Metabolic Power: 15w	Internal indicators %HR max= 85 RPE: 5	External indicators Distance Speed > 19 Km/h: 300m Metabolic Power: 12w	Internal indicators %HR max= 85 RPE: 5
	TRAINING LOAD: Based on speed indicators 200x5=1000 u.a. Based on metabolic power indicator: 15x5= 75		TRAINING LOAD: u.a. Based on speed indicators 300x5=1500 u.a. Based on metabolic power indicator: 12x5= 60	
	ATHLETE PHYSICAL PERFORMANCE INDEX: Based on speed indicators: 200/85= 2,3 Based on metabolic power indicator: 15/85=17,6%		ATHLETE PHYSICAL PERFORMANCE INDEX: Based on speed indicators: 300/85= 3,5 Based on metabolic power indicator: 12/85=14,1%	

7. CONCLUSION

A lack of a “gold standard” that allow to determine intensity in soccer makes difficult explaining the intensity concept and, consequently, become more difficult to select appropriate indicators to assess the performance. The intensity concept should refer to a relative approach that include both internal and external perspective. Furthermore, considering only one approach (internal or external) cannot explain whether a task or a training session can be considered intense or whether the athlete's effort can be considered as “intense.” For this reason, practitioners need to evaluate both internal and external indicators in order to understand if a training session can be considered intense or not for an individual athlete or whole team. Practitioners should use several external and internal intensity indicators during the monitoring process because each of them explains a partial component of soccer physical performance. The metabolic power and derived measures along with speed indicators should be used to monitor and assess soccer tasks underlining the fundamental role of accelerations in soccer. Therefore, the exclusive application of speed-derived indicators to monitor intermittent activities should be limited. It worth noting that playing positions, along with other aspects, influence high-intensity match performance. In this perspective, soccer intensity can be defined as “the result of the

performance provided by a measurable and comparable amount of work relative to the time, operationalized through factors external and internal to the athlete.”

PRATICAL APPLICATIONS

Understand the intensity concept allows practitioners to better schedule and assess soccer training during micro- and macro- cycle periods. Intensity derives from a multidimensional construct including both internal and external concepts. Therefore, (1) the application of a single indicator cannot fully explain all the intensity’s aspects in soccer training. Hence, several variables or indicators are required to holistically assess athletes’ task performance. Moreover, (2) these variables could be also operationalised following different approaches (i.e., internal and/or external) in order to have a combined score that permits to easily evaluate the soccer players’ performance (i.e., EL/IL ratio).

The new conceptualization of intensity, (3) defined as “the result of the performance provided by a measurable and comparable amount of work relative to the time, operationalized through factors external and internal to the athlete”, is linked to the concept of relationship and comparison explaining the meaning of “measurable quantity of something” (e.g., energy or training results). Intensity should include volume indicator (e.g., time or distance) that is relates to a reference measure. In this prospective, the concept of intensity is strictly associated to training load calculated multiply intensity and duration of training. There is a broadly different approach considering the external or internal intensity approach whereby each one provides fundamental and indispensable aspects that allow understanding the effects of training. In order to better understand the concept of intensity, coaches should (4) relate the internal response of the athlete with the product of training in terms of speed, distance, power. Moreover, each indicator reveals core but partial performance components whereby practitioners should take into consideration several other external intensity indicators to comprehensively assess soccer performance (including both speed and accelerations derived measures).

2.2 Translating player monitoring into training prescriptions: Real world soccer scenario and practical proposals

Pillitteri, G., Clemente, F. M., Sarmiento, H., Figueredo, A., Rossi, A., Bongiovanni, T., Puleo, G., Petrucci, M., Foster, C., Battaglia, G., & Bianco, A. (2024). Translating player monitoring into training prescriptions: Real world soccer scenario and practical proposals. *International Journal of Sports Science & Coaching*, 17479541241289080.

1. INTRODUCTION

Soccer performance is multifactorial, characterized by interdependent aspects, such as physiological, psychological, technical, and tactical, along with contextual factors that should be considered during training practice. In recent years, training load (TL) [referring also to match load] monitoring practices have increased through Electronic Performance and Tracking Systems (EPTS) such as Global Positioning System (GPS), with the aim of better understanding the physical demands of soccer. Given the multifactorial nature of soccer physical demands, several indicators derived from monitoring practice should be considered by practitioners to better understand the effects of training and matches (76, 77). TL has been conceptualized by Impellizzeri et al., as an external load (EL) wherein the activities performed by the players (such as total distance [TD], accelerations and decelerations) determine an internal athlete's response defined as the internal load (IL) (30).

Due to the multifactorial nature of soccer performance, there is no single gold standard of reference for performance outcome (17, 30, 213). Indeed, it would be impossible to consider a single TL indicator to evaluate performance which is based both on the match-demand (e.g., high-speed running [HSR] distance) and on the physiological component (e.g., energetic system involved such as metabolic and neuromuscular factors related to players responses). In this way, the activities effectively performed during match/training (i.e., EL) and the players' physiological responses (i.e., IL)) (2) has been conceptualized (30) as highlighting the different demands among playing position (77, 145, 153, 201).

Although soccer performance has been assessed through several physiological-related factors, as well as considering match-demand-related indicators derived from GPS such as external load indicators (e.g., TD, HSR, acceleration, decelerations, metabolic power) and internal indicators

(Rating of Perceived Exertion [RPE], oxygen consumption [VO_2] and Heart Rate [HR]) (30), some studies have investigated EL and IL as integrated approaches implementing new indices or ratio for IL and EL (214) aiming to assess the athlete's performance and fitness status. For example, authors computed a Effindex (as the ratio between mean speed in $\text{m}\cdot\text{min}^{-1}$ divided by the mean exercise intensity [%HRmax]) for every entire first half of the match to quantify the match stimuli dose-response (214, 215). They reported that the higher the overall running performance during the entire game, the higher the Effindex (214, 215). However, to the authors' knowledge, no studies have investigated the association between EL/IL ratio and injury risk (IR) despite a correlation between low fitness status (evaluated through EL/IL ratio) and IR being reported by literature (2, 216-219).

Despite controversial results (21), studies have consistently revealed a positive correlation between TL and injuries (220). However, the cause-effect relation to explain a multifactorial phenomenon such as sports injuries is challenging (5, 28, 132, 221). Therefore, they may require complex studies supported by machine learning [ML]-based analyses (5, 13, 80, 106). In light of this, Kalkhoven and colleagues (5) have reported that the appropriate interplay among IR factors, such as EL, and tissue loading response, must be understood from a complex multifactorial perspective. However, interpreting the association or relationship between TL and match load and injuries or performance require a holistic approach, considering the interconnection between each risk factor, to bring the scientific evidence into the "field" practice (5, 132, 221).

The literature shows controversial results concerning the relationship between TL and injury, revealing statistical limitations and biases among studies (132, 221, 222). For example, Drew et al. (223), have reported moderate evidence for relationship between TL (considering both EL and IL indicators) and risk of injury. In the same way, Jasper et al. (21) reported a weak evidence when both EL and IL load were related to injuries, suggesting that the implementation of continuous TL monitoring combined with the individual physiological characteristics such as (speed or endurance player) (173) is essential to examine the relationship between TL, physical fitness status (high/low fitness level) and IR with the aim of tailoring the training program based on individual needs (224-226). The relationship between TL and injury is mediated by several factors (219, 227), in the real world scenario, TL management represents the main strategy to implement good training practice aiming to enhance physical performance while reducing IR (2, 5, 30, 132, 216, 222, 228-230). In light of this, Gabbett (216) reported that appropriate TL management including a training prescription of high TL, avoiding TL spikes (i.e., avoiding increasing acute TL [absolute workload performed in 1 week]) and monotony (i.e., defined as the daily mean workload divided by the daily workload standard deviation) (231). In the same way, enhancing chronic load (4-week average acute workload)

may improve players' fitness status and protect them from injuries (232). Indeed, when an athlete is subjected to appropriate training stimuli (according to training principles such as graduality, variability, load modulation, frequency), following the supercompensation criteria (derived from knowledge of physiology), the level of fitness will chronically increase protecting him from injuries.

Worth noting, monitoring both EL and IL allows the training program to be addressed based on an individual approach (225, 230, 233). Although studies have examined the implications of the TL on training outcomes such as injury and physical fitness (21, 23, 26, 27, 180, 220, 223), results are conflicting and often lead to conceptual errors or misinterpretations where a lack of cause-effect relationship lead us to apply a more holistic study design including TL monitoring data, athlete's physiological characteristic (e.g. tissue load tolerance), well-being assessment, environmental factors (5) analysed through Machine Learning approach (5, 13, 80).

We highlight that training prescription (8, 173) is supported by training/match load monitoring, including the characteristics of individual players (225, 234), where athletes are driven by an objective evidence (2) that play an essential role in increasing physical performance while reducing IR (26-28, 155, 220, 235). In this sense, to take evidence-based decisions influencing training prescription, practitioners should understand the complex relationship between TL and training outcomes (physical fitness, injury, and fatigue (17, 21, 236)). Physiological information should also be considered during the exercise prescription process as adaptations occur when appropriate and individualized stimuli (i.e., external activities) are administered to athletes (30, 61, 99, 132, 237).

Revé et al., 2020 (238) have proposed a practical approach concerning the use of GPS data for TL monitoring in a “real world” soccer context by suggesting that the planning of external TL should be carried out on a monthly, weekly, and daily level in order to improve physical performance of the team, based on individual approach. In fact, based on the evaluation of the TL including both the EL and IL and EL/IL indices, it is possible to tailor the training program based on the specific needs of each player (30, 225, 230). Accordingly, correctly interpreting the TL data collected, accurately communicating the results within the staff (i.e., informed-making process) is essential to increase the physical performance of each player, and consequently of the entire team.

This narrative review aims to provide an overview on training monitoring and training prescription to improve or maintain (239) soccer physical performance considered as key factors to reduce non-contact IR. In this context, we provided two conceptual frameworks. The first concerns the relationship between TL (based on application of EL and IL) and IR. The second is based on the monitoring process and its implication on informed-making process related to training prescription.

We also provide practical examples on the relationship between the TL and soccer physical performance to understand the different concepts behind the use of the operationalization based on specific EL and IL indicators. Moreover, we reported relevant key questions and relative answers that fitness coaches, supported by sports scientists, should consider on monitoring process and training prescription to improve the informed decision-making process and communication within the technical and medical staff.

1.2. TRAINING LOAD IN SOCCER

TL has been defined by Impellizzeri et al., 2019 as “the input variable that is manipulated to elicit the desired training response” (30). Two essential components have conceptualised training load as being either external and/or internal. EL refers to the amount of activity performed by players/athletes generally described by distance (with different speed thresholds), number of accelerations, decelerations, and metabolic power in a given training session or official match. EL is determined by the physical work prescribed in the training plan. Activities performed determine the athlete's psychophysiological response corresponding to the IL. In soccer, it has been described by HR, Rate RPE scale or lactate blood concentration (145).

It is worth noting that, given a lack of a gold standard, the training load may be quantified by several indicators, including the EL or the internal response during the exercise (30, 132). For further information on the TL and its variables, we refer the reader to Impellizzeri et al., 2019 (30), and McLaren et al., 2017 (22). Following Gabbett et al., 2017 (2), we highlight that monitoring of training load (both EL and IL) represents an essential practice that should involve the whole staff team (both technical/physical and medical) to optimise training prescription aiming enhancement of physical performance while reducing IR.

Nevertheless, several conceptual questions considering both internal and external intensity indicators in soccer have been reported in the literature (14, 175, 177, 230). For example, studies found that S-RPE and HR-derived measures were more associated with volume (i.e., Total Distance, Low Running Intensity) than intensity indicators (175, 177) highlights that this correlation is lower when intensity thresholds increase. Also, Scott et al. (2013) reported that cardiac response is more associated with distance covered at low speeds than the one covered at high speeds (178, 179). As a matter of fact, HR and RPE underestimate the IL response derived from anaerobic metabolism

because this mechanism is mainly involved during short, high-intensity activities (178). Hence, RPE could underestimate the workload sport specific tasks such as SSG because it may be more related to non-specific metabolic activities in which HR show a linear response (85, 178).

Moreover, concerning EL indicators, evaluating soccer training/match using speed measures allows for assessing only a partial component of external physical demand (70). In this way, Gaudino et al. (2015) reported that the use of metabolic power for assessing physical performance demands (derived by speed and accelerations) is more appropriate concerning the use of only speed indicators (85). Hence, both categories of EL (i.e., speed and acceleration) should be considered as they may be more related to S-RPE than the use of only one alone to monitor training in soccer (180).

1.3. SOCCER PHYSICAL PERFORMANCE

From the work-setting perspective, performance has been defined as “the accomplishment of goals by meeting or exceeding predefined standards” (44). Actually, performance assesses how much ‘work’ someone has performed compared to a gold standard. At the same time, soccer performance results from the interaction between technical, tactical, cognitive, psychological and physiological factors. In this narrative, we will refer to “soccer physical performance” which measures how much ‘physical work’ an athlete has performed compared to a gold standard (i.e., match-demand or physiological demand). Different indicators related both external (imposed match-demand), internal (physiological response to a given imposed stimulus) factors and EL/IL ratio (athlete-related physical performance) allows us to assess “soccer physical performance” since both the physiological and match-demand components are implicated in soccer performance. Accordingly, it has been conceptualised three components related to soccer physical performance: (1) *match-demand* (i.e., an external component such as distance, speed, accelerations, metabolic power, change of directions, and strength); (2) *physiological-demand* (internal component such as heart rate, maximal oxygen consumption, rate of perceived exertion); (3) *athlete-related performance* refers to an individual internal response to a given EL. The relevant component of soccer physical performance is an essential part of the current review and will not be further discussed here. We suggest to refer to Stolen (61), Harper (62), Rico-González (64), and Sarmento (65).

2. THE IMPLICATION OF TRAINING MONITORING IN SOCCER

Assessing training monitoring data can be considered as a support for practitioners to optimize training process ensuring that athletes appropriately adapt to the training program and cope with match-demands, which could reduce IR (240). Gabbett et al., (2) have provided a practical guide to interpreting and applying training monitoring data. They have suggested considering a combination of external workload, internal workload, perceptual well-being, and readiness to train/compete as delivering more meaningful individual training prescriptions compared to data derived from any single athlete monitoring tool/indicator (2).

Coyne et al., have reported some issues and limitations related to subjective TL calculation (e.g., RPE) as both volume and intensity indicators should be considered accordingly (229). Indeed, they have recommended using the training impulse (the product of training volume and intensity factors) for IL and EL, rather than a singular volume or intensity factor. This allows comparing “apples with apples” avoiding methodological differences among studies which make comparisons difficult inducing possible misleading interpretation (229). In addition, authors suggested to consider relevant analysis such as the lagged effect of multiple concurrent time series (e.g., TL and physical performance) to better understand the TL implication on soccer training (104, 229). Moreover, practitioners should also use methods of TL model calculation (e.g., rolling averages [RA] and exponentially weighted moving average [EWMA], over different acute and chronic periods, varying “fitness”- “fatigue” decay rates) that is most strongly related with physical performance and IR (104, 229).

As reported by Coyne et al. (229), inconsistent findings examining the relationship between TL and injury and performance (241) may be related to TL (computed as duration x intensity) that is defined as “a relatively simplistic and somewhat limited tool for accurately modelling training responses in elite athletes” (231, 242, 243). According to Renfree et al. (242), TL (given by the product of exercise intensity and duration) may be limited as does not account for non-linearities in the biological response to stress. In agreement with the previous authors, the TL may not be fully satisfactory even if it remains the only tool available to monitor soccer training. Rather than considering the use of TL as ‘simplistic,’ we believe that, given the complexity and multifactorial nature of both soccer physical performance and the “physiology” of human beings, it would be illogical trying to calculate the TL based on one indicator alone (considering both internal and external) during the monitoring process. Accordingly, seems cognitive bias consider a single TL indicator as

“causative” of injuries. Moreover, “intensity” and “performance” concepts should be well defined to provide consistency among studies reducing methodological and conceptual bias (213).

Thus, it is recommended that practitioners should rely on traditional training principles (e.g., overload progression (1, 228, 244)) and adjust the TL based on athletes’ responses (221). Although we recognize a lack of causality and direct connection between TL and IR, especially when considering a single indicator of internal or external load, keeping in mind training programming as a primary injury prevention strategy. We strongly suggest controlling and manipulating workload in order to reduce IR accordingly with previous studies (i.e., Gabbett 2017 (2) and Windt et al., 2017 (219)). For example, despite the fact that high-speed running distance has been associated with IR (245-247), being the aetiology multifactorial (130, 227), it would not make sense to consider it a cause of injury. Indeed, it can only predisposed players (i.e., weak athletes subjected to maladaptation due to non-optimal training planning, previous injuries, etc.) may get injured when exposed to large volumes of high-speed running. Logically, even if a direct cause between workload and IR does not exist (132), the workload, especially whether it is not well managed, could be highly implicated in the onset of injuries. Indeed, injuries occur during workload load exposure (i.e., training or match) (118, 128, 248). Accordingly, practitioners should focus on TL management (30, 132, 221, 244), where monitoring practice (i.e., data-driven approach) allow to take objective information on TL, aiming to enhance physical performance while reducing IR.

3. SOCCER TRAINING PRESCRIPTION: PROGRAMMING STRATEGIES

Even if the scientific community has provided useful contributions, practitioners should take into consideration that the science and practice of periodization is largely based on the hypothesis based on casual observation (249, 250) where the data-driven approach has shed light and supported the concept of training prescription (2, 5, 30, 77, 106, 132, 145, 153, 251, 252). Starting from the knowledge provided by exercise physiologists, evidence of specific adaptations to imposed demands (SAID) (253) should be kept in mind during the training prescription phase. The SAID principle allows coaches to facilitate neural and metabolic adaptations, as well as muscle fibres changes for increased strength and refined motor skill. Hence, to appropriately adapt muscles, the frequency and intensity of the exercise must be adequate in order to provide a “overload” for the target muscle or muscle groups related to match-demands (254). Thus, it is easy to understand that there is a significant difference between track and field and team sports athletes that must be considered in the planning phase (8). In soccer, given the high-intensity physical demand imposed by the match (i.e.,

cardiorespiratory, metabolic, neuromuscular and cognitive function), coaches have focused on High Intensity Training (HIT) methods (33). In this way, Buchheit and Laursen have carried out a review on HIT training (8, 33) reporting theoretical and methodological insight on HIT. HIT involves “repeated short (<45 s) to long (2–4 min) bouts of rather high-intensity exercise interspersed with recovery periods” (33, 228).

In order to maximize daily and/or weekly training periodization, HIT prescription consists of the manipulation of at least nine variables (e.g., work interval intensity and duration, relief interval intensity and duration, exercise modality, number of repetitions, number of series, between-series recovery duration and intensity) (8, 228). Hence, when programming HIT, both cardiopulmonary responses, anaerobic glycolytic energy contribution and neuromuscular load should be considered to maximize the training outcome. In team sports athletes, the physiological effort induced by HIT along with other physical and technical/tactical sessions should be considered to avoid overload and optimize adaptation (i.e., maximize a given training stimulus and minimize musculoskeletal stress and/or IR). We highlight that a significant difference concerning HIT training methodology between track and field and team sport athlete exists. Indeed, while running training prescription can be determined a-priori (considering both external and internal load) for endurance runners (255), accurate soccer-drills programming is challenging due to the intrinsic variability (231) of soccer activity compared to HIT running drills as shown in Supplementary files.

Accordingly, soccer training prescription required an appropriate knowledge of physiological (both metabolic and neuromuscular) response induced by each specific HIT (including Small Sided Games [SSG]) format (228, 233, 252, 256). In order to appropriately support the training prescription based on the training methodologies principle (1, 33, 46, 61, 257) and applied physiology knowledge (253), practitioners should take into account a large amount of external load data (provided by EPTS devices such as GPS or Inertial Sensor Device [ISD]) to classify appropriately each drill and programs training day, microcycle and mesocycle in soccer (238). From this perspective, player’s density on the pitch (i.e., area per player, m^2/player) has been considered a key factor of the SSG that determines different EL and estimates physiological match-demands in elite soccer players (252). For example, Riboli et al., have reported that to achieve higher TLs at high speed, a higher density is necessary regardless of the type of SSG (252, 256). Moreover, larger area per player determines higher total distance, high and very HSR distance and sprint. Moreover, a minimum of $\sim 200 \text{ m}^2/\text{player}$ may appropriately determine the high-speed running and sprint events in youth players (258). Interestingly, replications of the whole official match ($\sim 357 \text{ m}^2/\text{player}$) including the sprint distance, a density of $\sim 288 \text{ m}^2/\text{player}$ is required while a $\sim 340 \text{ m}^2/\text{player}$ has been recommended to replicate

the official match peak demands (256). A great contribution on SSG prescription in soccer has been provided by Rampinini et al., 2007 that have examined the effects of exercise type, field dimensions, and coach encouragement on the intensity and reproducibility of SSG (259).

Authors found that by using different combinations of these factors, coaches could modulate exercise intensity within the high-intensity zone and control the TL. Clemente et al. have presented a theoretical methodological recommendation on SSG periodization (260). Specifically, it was suggested that changing the number of players, field dimensions, and task constraints could possibly stimulate different physiological responses. It is worth noting that SSG do not fully replicate the physical stimuli derived from match-demand (261). Indeed, Pillitteri et al., have investigated the EL differences between specific types of soccer drills (including SSG) and official match for each playing position using a supervised Machine Learning approach (262). Authors found that the performance model for each role in SSG seems completely different compared to official match as the players' playing positions are not distinguishable during SSG as the maintenance of a specific role in these kinds of exercises is not required (262). Accordingly, care should be taken when prescribe sport-specific task such as SSG within a soccer microcycle.

Buchheit & Laursen (2013) (8) have reported the application of the Thibault model (263) to select the most appropriate HIT sessions obtained while manipulating work interval duration and the number of repetitions. Authors have highlighted that the session with high metabolic and neuromuscular responses (targeting long-term adaptations) and the time needed to recover from the session should be considered to 'fit into the programming puzzle' (228). Hence, some practical examples of HIT sessions to optimise the time spent at VO_{2max} ($T@VO_{2max}$) have been provided, focusing on the strategy to appropriately manipulate the training variables aiming to involve higher amount of anaerobic glycolytic energy contribution associated with higher neuromuscular and musculoskeletal load. In addition, authors reported some relevant practical considerations, supported by physiological knowledge and training principles (8, 61, 80, 92, 173, 228, 237, 253), suggesting that HIT sessions should be separated by 48 to 72 h (depending on the expected metabolic and neuromuscular load) (8, 228). They are generally followed by an easy session (i.e., active recovery, low intensity aerobic training, low intensity soccer drills, low neuromuscular effort) the following day to accelerate post-HIT metabolic and neuromuscular recovery. Moreover, as suggested by the framework by Sandford et al., 2021 (173), high-intensity interval training formats should be tailored to the athlete's locomotor profile accordingly (i.e., 'speed', 'endurance' or 'hybrid' profiles). Authors have shown the importance of employing the anaerobic speed/power reserve (ASR/AP) required to individualise training appropriately (173). Indeed, as reported by Hostrup & Bangsbo (73),

implementing speed endurance training such as all-out efforts or sprinting of typically 10- to 40-s duration with longer recovery periods, positive adaptations relating to anaerobic energy systems, ion handling, and fatigue resilience have been observed, allowing to enhance performance in elite soccer players during the late preparation phase and competitive season.

In summary, many factors should be considered when planning the microcycle in elite soccer, including session content, orientation and load, or when to rest players, bearing in mind that there are many approaches among coaches and different cultures (244, 264). As reported by Buchheit et al., 2023 (1), “The Original Guide to Football Periodisation – Part 1”, by R. Verheijen in 2014 (265) is the first and by far the most complete source of information on soccer programming along with the FC Barcelona (264). An appropriate microcycle soccer periodization is challenging as several factors should be considered in complex relationship between technical-tactical and physical performance components to prescribe training programs appropriately.

In this way, a review carried out by Buchheit (7), explored various principles useful for programming the training microcycle on the basis of scientific evidence which has the task of “informing” the experts to make decisions. Specifically, author highlighted the microcycle structured in three phases (recovery, acquisition and reduction) based on the scheduling of the matches (i.e., duration of the microcycle). The second principle addressed rest day mapping, emphasizing the rest day placement strategy, particularly effective in (actual Match Day) MD+2, in order to reduce injury rates within different microcycle lengths (and probably also allow substitutes to train on MD+1). The third point explored the management of post-match recovery and compensation training, suggesting post-match (MD+1) upper body training as compatible with recovery, with potential benefits varying between players and underlining the need compensation for high intensity and speed training (at MD+1) to maintain the performance of substitutes and reduce the risk of injury (1, 7, 244). The fourth point is important as it goes into the merits of weekly training loads and the management of HSR. The information provided by scientific evidence identifies the optimal ranges of training load (60-90% of the match load, achieved through football training) to balance the improvement of performance and the reduction of injuries (7, 79, 244, 266). A paramount factor concerns the high-speed peaks, as a strategy to reduce the risk of injury. Indeed, the importance of training at near-maximum speed (>95%) in MD-2 may be associated with a reduction in injury rates (79, 266). Finally, strategic tapering leading up to the match was suggested, as a balance between moderate and light load on the pre-match days (MD-2 and MD-1) with a greater focus on recovery leads to optimal performance and injury prevention (1).

Implement an appropriate training program during a soccer season is challenging as different component such as both physiological aspects related to soccer players and the references values derived from match-demand knowledge should be considered. For examples, professional players to regularly cover total distances ranging between 10-13 km of which around 900 m and 250-300 m travelled at HSR (speed ranging from 19.8 km*h⁻¹ to 25.2 km*h⁻¹) and sprinting (speed ≥ 25.2 km*h⁻¹), respectively (37, 58, 59). The importance of HSR and sprinting distance has been recently discussed in a systematic review [34]. Specifically, during official matches, HSR and sprint running distances ranged from 618 to 1,001 m and 153-295 m, respectively, in professional male soccer players. In this perspective, Miguel et al. (38) carried out a review on load measures in training/match monitoring in soccer, while Oliveira et al. (78) reported detailed reference values for external and internal training intensity monitoring in young male soccer players. However, match-demand differences do exist between and within specific contexts such as professional and amateur level. Indeed, HSR distance ranged from 106-539 m, (12-61% match loads) at the professional level [14,15] compared to 6-135 m (1-30% of game loads) in collegiate players [17].

Starting from the reference values offered by match-demand, the amount of load (how much load should be carried out during a specific training section?) that should be obtained during each training section within the micorcycle structure represent a complex task for practitioners. Accordingly, periodized exposure to both HSR and sprinting within the microcycle of a soccer season could help players to withstand the match demands while reduce injury risk (67). In this perspective, an optimal training-to-match HSR ratio should be considered, despite high variability exists due to different training methodologies and context among teams. In this way, Clemente et al. (267) investigated the training-match ratio (calculated based on total distance, player load and total number of high (> 3 m*s⁻²) accelerations and decelerations) and found that, on average, training sessions represent 1.8 times the effort expended in a single match. However, variability significantly exist depending on the player's position and the number of training sessions per week (268).

4. DISCUSSION AND IMPLICATIONS

To achieve our purpose, this section is structured as follows: section 4.1 delves into the monitoring process and data management, reporting some theoretical concept on training monitoring and data interpretation and communication. Section 4.2 explores the relationship between EL and IL training emphasizing the differences between training load and physical performance trough practical examples. Section 4.3 reports a conceptual framework on players readiness and injury risk while

section 4.4 describes a conceptual framework on the informed-making process starting from training prescription, trying to answer some question as follow: how should practitioners start prescribing soccer training? From what perspective should practitioners prescribe training? In this perspective, section 5, considered as a core of our work delves into the theoretical aspect of training prescription. Section 4.6 provides some practical application, supported by scientific evidences, on the ways in which practitioners should report the “physical outcomes” derived from monitoring, relating to the match/training; section 4.7, delves into the complex relationship between the physical trainer head coach or the head managers, suggesting practical solutions to reporting the information derived from monitoring.

4.1. MONITORING PROCESS AND DATA MANAGEMENT

TL management is a relevant practice that allows optimal design of training to maximize physical performance while minimizing IR. TL management includes prescription, monitoring, and adjustment of EL and IL, for which several practical guidelines have been developed. Indeed, in 2006 the International Olympic Committee consensus statement on load in sport and risk of injury (155) offered practical guidelines for load management. In this way, athlete monitoring systems should be supported by appropriate data analysis and interpretation to support the rapid reporting of clear, appropriate and scientifically valid feedback for teamwork (i.e., staff) (269).

Different analytical methods and tools have been implemented to monitor soccer players such as GPS (139) and RPE (164). Several factors should be considered when collecting the data, including methods for determining meaningful changes such as Standard Deviation (SD), typical error, effect sizes, smallest worthwhile change (SWC), coefficient of variation (CV) and magnitude-based inferences (MBI) and various data visualisation approaches by using specific software such as Power BI® (Microsoft, Redmond, Washington) are also available (269). In this regard, the ability to communicate and present relevant information to coaches and/or managers is the basis of an effective monitoring system. A review carried out by Thornton et al., 2018 (269) reported a range of data analytical methods commonly used in applied and research settings and can be used to determine and interpret meaningful changes in data, assisting in advising informed-making.

Moreover, the authors have provided various data visualisation concepts and methods to improve the quality of the monitoring system through effective communication of relevant information (269). Importantly, as reported by Thornton et al. (269), “these data and the meaningful information derived should be used, simply, to inform coaches regarding athlete status but should not dictate the informed-making process”. For examples, during a specific training session with the aim

to reach a given amount of HSR distance (based on an individualised approach which takes into account reference values derived from the match-demand), a data-driven approach allow to support the training prescription (80, 216, 228, 244, 270). Indeed, it is possible to administer an integrative work (considering a training/match ratio of HSR and sprinting with a range of 0.8-1.2) such as sprinting (e.g., 2-3 reps of 30m with > 90% of maximal velocity with 45 s recovery in between reps) (271) to reach the HSR quantities set during planning phase (59, 80). In this way, practitioners should consider to monitoring EL based on an individualized approach by adjusting the indicators threshold based on a combination of maximal aerobic speed (MAS, derived from the Yo-yo Intermittent recovery test level 1), maximal sprinting speed (MSS, derived from the maximal speed reached during training) and anaerobic speed reserve (ASR) to respect players' individuality (272).

4.2. RELATIONSHIP BETWEEN EXTERNAL TRAINING LOAD AND INTERNAL TRAINING LOAD: DIFFERENCES BETWEEN TRAINING LOAD AND PHYSICAL PERFORMANCE

Table 2.5, Figure 2.1 and Table 2.6 report information to better clarify this complex relationship by providing more insight into the management of data derived from training and match monitoring. In detail, the examples provided in Table 2.5 and Figure 2.1 show that each EL indicator provides specific and essential match/training information. Based on these examples, we suggest: 1) to apply both EL and IL indicators during the monitoring phase; 2) to assess the athlete's fitness status by using EL/IL ratio (14, 215) including the indicators deemed appropriate (e.g., speed-related and acceleration related [for example, Total Distance/RPE]); 3) to compare the athlete TL (e.g., considering different EL indicators such as TD, HSR distance, intense accelerations and decelerations, and metabolic power) with references provided by official matches; 4) to compare the athlete TL (e.g., considering different EL indicators) with references provided by official matches specific for playing position (e.g., midfielder vs midfielder); 5) to compare the athlete TL (e.g., considering different EL indicators) with references provided by the average provided by previous training sessions performed in the same day of the microcycle (e.g., [MD]-2 vs average MD-2 [assessed throughout the season]). Moreover, based on the outcomes reported in the Table 2.6, practitioners should consider: 1) to assess TL and physical performance of official match by including volume and intensity EL indicators; 2) to include EL/IL ratio (e.g., TD/RPE) to assess the athlete's fitness status taking into account individual variations.

4.3. RELATIONSHIP BETWEEN ATHLETE FITNESS STATUS AND LOAD: CONCEPTUAL FRAMEWORK ON PLAYERS READINESS AND INJURY RISK

As reported by Jeffries et al. (17), a conceptual framework “synthesizes evidence, assists in understanding the phenomena under investigation, informs future research and acts as a reference guide in practical settings,” including explanations of the relationships between the construct to be measured (34). It can be carried out through visual representation and logical structure, illustrating presumed relationships between key concepts, constructs, or measures (e.g., EL and IL indicators). In this way, our conceptual framework includes an integrative synthesis of the literature and analysis of existing frameworks linked to information and concepts from previously established models and theories. Starting from the model used by Gabbett et al. (2) on athlete monitoring data in the sporting environment, we combined athlete fitness status (given from the external and internal load ratio (83, 86, 197, 273)) with workload (considering or a single indicator or a more appropriate parameter such a global load “score” (274) which includes several EL and IL load indicators derived from players monitoring). However, more sophisticated analysis such as machine learning approaches, could calculate a global load score (87, 275) (Figure 2.2) allowing trainers to prescribe training following an individualized approach. In detail, the Principal Component Analysis was used to reduce the feature dimension space in order to aggregate features to summarize the training workloads performed by soccer players during training and matches. This simple relationship based on data monitoring simply helps to establish whether an athlete is ready to compete (both training or match) or may be at high IR. For example, suppose an athlete shows a low fitness status (i.e., has performed a low rate of external activity with a relatively high internal response) and presents a high-performance score (i.e., high overall performance score derived from high neuromuscular effort for a long duration). In that case, this athlete may be at high IR as he would not be prepared to withstand the stress imposed by training/match demands. Accordingly, practitioners can prescribe training based on an individualized approach. The combination of EL/IL ratio with load represent a simple way to understand the athletes’ readiness in a daily routine while different strategies such as laboratory and on-field test (e.g., submaximal fitness test during warm-up) (276) can be also applied to determine whether an athlete is ready to train or compete. Accordingly, a daily routine of TL monitoring, in comparison with laboratory and on-field tests, which present disadvantages such as cost, human resources, time, complexity, equipment), should be guarantee during a soccer season.

4.4. CONCEPTUAL FRAMEWORK: FROM TRAINING PRESCRIPTION TO THE INFORMED-MAKING PROCESS

Although previous published conceptual frameworks (2, 8, 17, 30, 33, 173) have provided fundamental theoretical and practical insight, some misconceptions, confusion, and lack of practical examples in TL monitoring and training prescription area may still exist. For example, how should practitioners start prescribing soccer training? From what perspective should practitioners prescribe training? The diatribe between the training prescription based exclusively on the physiological approach as opposed to "data-driven", where the reference match is made considering the external load, is still open. In this session, we briefly reported a new framework concerning the relationship between player monitoring process and informed-making on training prescription. Figure 2.3 describes the monitoring process to help practitioners make the best possible decision on training prescription to optimize adaptation (i.e., enhance physical performance) and reduce IR. In detail, our revised conceptual framework highlight that several factors should be considered to implement an appropriate training prescription including match-demand, physiological-demand, contextual factors, training methodology principles, individual athlete knowledge, athlete profile and information derived from monitoring process.

4.5. TRAINING PRESCRIPTION

To appropriately implement soccer training prescription, such as HIT game-based, practitioners should refer to the support provided by the EL monitoring data (derived from EPTS devices (238)), the information provided by scientific literature and the knowledge of training principles and applied sport physiology (277). Appropriate training prescription is a complex practice that could lead to positive as well as negative adaptations. Nevertheless, TL data provide a useful support to appropriately prescribe training (2, 238, 240). Are we sure that the indices and indicators most used among practitioners are always useful? Some suggestions on training prescription have been reported in supplementary file 1.

In detail, based on the outcome reported in the supplementary file 1, practitioners should consider: 1) to assess TL and physical performance of HIT specific drills (e.g., SSG) trough IL and EL by including metabolic and neuromuscular indicators; 2) to create a drills database, based on EL

monitoring, should be created to help during the training programming process of soccer specific training (i.e., technical-tactical session or drill).

Supplementary file 2 reports an example of general running training prescription based on external load indicators highlighting the poor applicability of the common TL calculation approaches. Indeed, the use of TL indicators along with EL/IL ratio could be poorly appropriate when compare works with different physiological demands.

Also, in supplementary file 3 we highlight that various formulas to calculate TL and physical performance may not be adequate to compare players who stress different physiological systems when perform general running exercises (e.g., HIT long interval). Conversely, as reported in supplementary file 4, when comparing the physical performance of two athletes who perform sport-specific exercises (e.g., SSG) with different physiological target, caution must be taken not to rely exclusively on the mathematical calculation of the TL or physical performance, considering the physiological target as well. Moreover, based on the great contribution provided by the framework carried out by Standford et al., 2021 (173), we have reported (supplementary file 5) a practical insight on training prescription considering the individual integrated approach (i.e., starting from the athlete profile knowledge, the physiology target definition and the expected IL, it is possible prescribe the external activities appropriately). Moreover, the comparison of two typologies of drills/exercises (i.e., SSG vs HIT based on general running short distance [intermittent exercise]) exclusively through TL indicators could be difficult and meaningless as present different physiological target stimuli (i.e., generic vs. game-based). Accordingly, caution should be taken, when prescribe training based exclusively on data-driven approach, while the physiological target of the drill should be considered.

4.6. HOW PRACTITIONERS SHOULD MANAGE THE INFORMATION DERIVED FROM MONITORING?

Best practice allows for optimisation quality of work within teams. How should sport scientists act to optimise the training process and obtain useful information from the data derived from monitoring? We provided a key point that allows prescribing training appropriately based on the contribution offered by data monitoring collected;

- Training/match monitoring and data collection;
- Data mining and data analysis;

- Data interpretation;
- Load analysis (internal and external);
- Performance analysis (compared to): reference official match; playing positions; teammates; opponents;
- Understand athletes' fitness status (internal/external load ratio);
- Understand athlete recovery ability and readiness;
- Informed-making process for training prescription.

4.7. HOW SHOULD THE PHYSICAL TRAINER ANSWER THE QUESTIONS OF THE HEAD COACH OR THE HEAD MANAGERS?

As reported by Ekstrand et al. (278), the four most common factors related to risk factors contributing to IR are the workload imposed on players, the player well-being, the quality of internal communication within the team and the head coach and the chief medical officers of clubs in the UEFA Elite Club Injury. The authors found that the quality of internal communication within a team was associated with both IR and player's availability. In this way, the internal communication quality within a team can be considered a fundamental strategy to decrease the IR (279). While head coaches and managers often focus on performance results, and the medical staff on injuries risks, physical trainers (i.e., sport scientists) are required to facilitate a communication bridge between departments. To avoid reporting incorrect and inappropriate communications, confusing performance, TL, and risk of injury, we have provided some key questions that physical trainers should consider:

- Which players had the best EL and IL in the last match?
- Was the last match more intense than the others already played?
- Which players showed the best physical performance (considering EL indicators per minutes) in the last match (i.e., best intensity)?
- Which players needs recovery?
- Which players needs extra physical training?
- Which players may perform the entire training session?
- Which players may partially perform the training session?
- Is physical performance associated with the match results?

In addition, we have reported the possible answer, including operational strategies to optimise TL and performance communications within the team (Figure 2.4).

5. CONCLUSION

Practitioners may need practical guidelines to understand the complex relationship between TL, physical performance and IR. Accordingly, a conceptual framework helps to clarify some theoretical and practical aspects such as training monitoring and prescription. While establishing a causal relationship between workload and injuries may not make sense given the multifactorial aetiology of injury, the accurate tracking of workload and the careful planning of training sessions, based on the indicators most related to physical fitness and fatigue, represents a good injury prevention strategy.

Appropriate, complete, and straightforward communication within the staff is also essential to increase the quality of teamwork to enhance physical performance while reducing IR.

In this way, in this narrative review we have provided an overview of the fundamental concepts related to the practice of soccer training (i.e., TL and physical performance), also focusing on injury prevention to propose practical applications by improving the informed-making process related to training monitoring practice, training programming and communication within the staff. Moreover, some practical examples have been provided to strengthen the theoretical concepts.

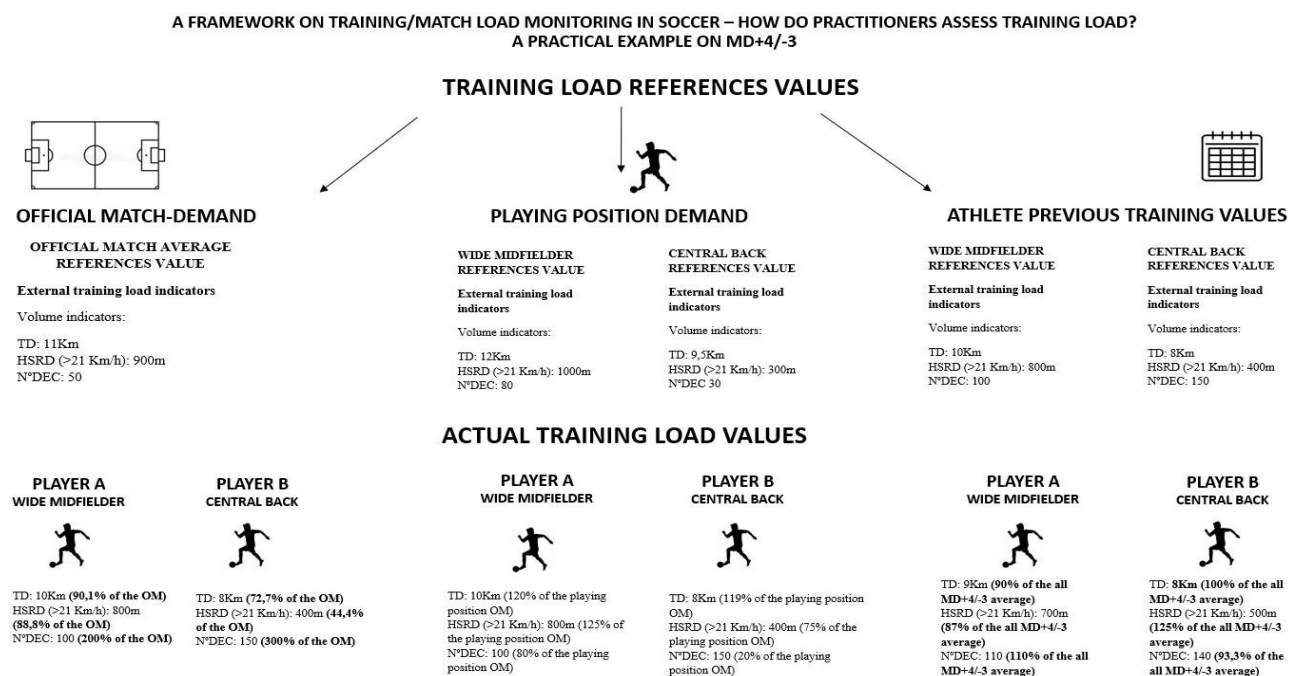


Fig. 2.1 Relationship between athlete fitness status, training load and injuries: a conceptual framework. Note: athlete fitness status derived from external and internal load ratio while “score performance” can be calculated by machine learning approach considering external and internal data collected (e.g., by using Principal Component Analysis). When athlete shows low fitness status, and high-performance score (i.e., performed a large amount of external activity such as high-intensity running) may not be prepared to withstand match or training-demand increasing his injury risk. Even if athlete presents high fitness status and low performance score may be at high risk of injury as could be not prepared (appropriately adapted) to cope match-demand. This framework can make sense in a long-

term perspective monitoring process. High fitness status and high score means that athlete is ready to compete (even if practitioners have to pay attention to tapering strategy to be implemented before the official match).

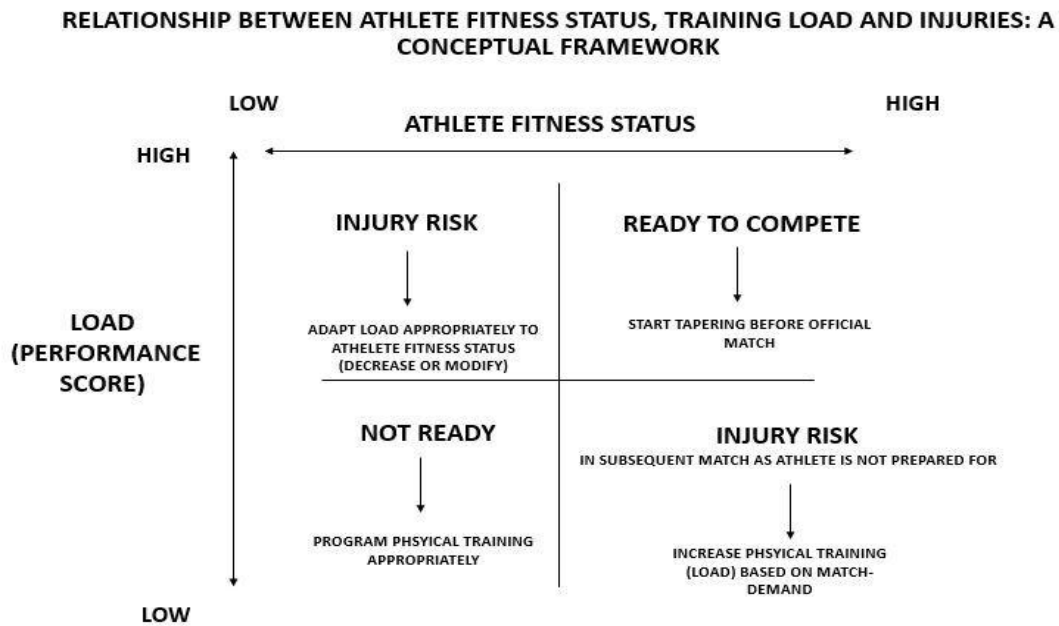


Fig. 2.2 Conceptual framework: from training prescription to the informed-making process. Note: based on revised previous works (i.e., Impellizzeri, Jeffries, Gabbett and Buchheit), we have reported a revised conceptual framework on training prescription informed-making process and load monitoring. Several factors should be considered to implement an appropriate training prescription including match-demand, physiological-demand, contextual factors, training methodology principles, individual athlete knowledge, athlete profile and information derived from monitoring process. In order to establish if some factors related to training should be changed or modify (during the planning phase), practitioners have to consider the aforementioned factors.

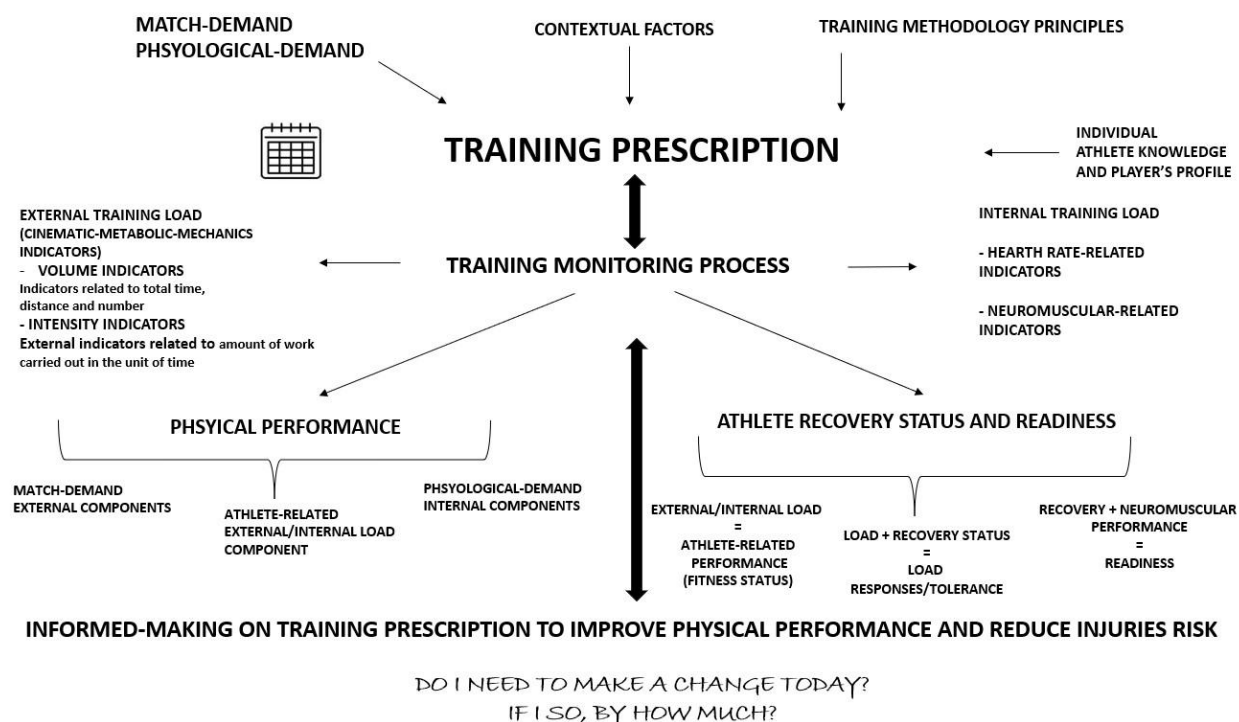


Fig. 2.3 Report «soccer physical performance outcomes» related to match/training.

HOW SHOULD THE PHYSICAL TRAINER COMMUNICATE WITH THE HEAD COACH OR HEAD MANAGER ABOUT LOAD AND PERFORMANCE?

ANSWERS THAT SHOULD BE GIVEN PROPERLY BY THE PHYSICAL TRAINER

- 1 Compare physical performance between players by highlighting differences between playing positions and consider different external and internal load indicators
- 2 Compare the physical performance of the actual match with the previous performance considering the different information provided by each indicator (external and internal)
- 3 Compare physical performance between players by considering different external and internal load indicators related to time
- 4 Determine if the athlete need recovery by assessing (1) recovery and neuromuscular performance: if athlete presents poor Recovery and poor neuromuscular performance (i.e., peripheral fatigue) he needs extra recovery; (2) if athlete shows high external Load and high internal load in the previous training section it is suggested to decrease the workload; (3) if athlete shows high workload and poor recovery the workload should be decreased or modified
- 5 Determine if the athlete needs extra physical stimuli by assessing recovery and neuromuscular performance: if player presents good Recovery and poor neuromuscular performance (i.e., peripheral fatigue) needs extra recovery
- 6 Determine if the athlete is ready to train by assessing (1) recovery and neuromuscular performance: if athlete presents good Recovery and good neuromuscular performance (i.e., peripheral fatigue) he is ready to train.; (2) if athlete shows low external Load and low internal load in the previous training section it is suggested to increase workload; (3) if athlete shows high workload and good recovery it is possible to continue training while if he shows low workload and good recovery the workload can be increased
- 7 Determine if the athlete need to participate partially in training by evaluating(1) recovery and neuromuscular performance: if athlete presents poor Recovery and poor neuromuscular performance (i.e., peripheral fatigue) he needs extra recovery; (2) if athlete shows high external Load and high internal load in the previous training section it is suggested to decrease the workload; (3) if athlete shows high workload and poor recovery the workload should be decreased or modified
- 8 Simply show your data with statistical analysis to show that exercise performance is not related to outcome (if so)

Fig. 2.4 A framework on training/match load monitoring in soccer – how do practitioners assess training load? – a practical example on MD+4/-3

2.6 Discussion

Chapter 2 explored the multifaceted concept of intensity, a cornerstone of modern soccer training methodologies. Utilizing a comprehensive narrative review and a robust conceptual framework, we investigated the intricacies of training load (TL) monitoring, dissecting the nuanced interplay between volume and intensity. Despite its critical role in optimizing performance, the concept of intensity in soccer remains ambiguously defined, leading to a fragmented understanding within both academic and practical domains. This lack of a universally accepted definition has resulted in inconsistent application and a proliferation of misconceptions regarding its measurement and significance.

Intensity is not merely a variable in training regimens but a pivotal determinant of performance in both training and competitive environments. It encapsulates the demands placed on players through high-speed running, accelerative bursts, and power-driven actions—elements that have significantly escalated over the last three decades in professional soccer. This trend reflects the escalating physicality of the sport and underscores the urgency for a precise conceptualization of intensity to enhance both training efficacy and competitive performance.

In our analysis, we highlighted the absence of a "gold standard" for quantifying intensity, a gap that complicates the accurate assessment and application of this concept in practice. To navigate this complexity, we proposed a dual-perspective approach, integrating both internal load (IL) and external load (EL) indicators. Internal indicators, such as heart rate and perceived exertion, provide insight into the physiological and psychological stress experienced by the athlete. Conversely, external indicators, including distance covered at various speeds and mechanical power output, reflect the objective demands of the task. A holistic evaluation of intensity requires the simultaneous consideration of both IL and EL to determine the genuine intensity of a training session or match scenario.

Our proposed definition of soccer intensity—"the measurable and comparable outcome of work performed relative to time, operationalized through factors that include both external demands and the athlete's internal response"—offers a comprehensive framework for practitioners. This definition emphasizes the necessity of a multidimensional approach to accurately capture the essence

of intensity, ensuring that training interventions are appropriately tailored to meet the escalating demands of the sport.

Building on this theoretical foundation, we presented practical proposals for training prescription based on player monitoring within real-world soccer contexts. These proposals underscore the importance of a structured monitoring process in managing the delicate balance between physical performance enhancement and injury risk mitigation. Although establishing a direct causal link between TL and injuries is inherently challenging due to the multifactorial nature of injury aetiology, our findings suggest that precise workload tracking and strategic planning grounded in reliable TL indicators can significantly reduce injury risks.

The interdependence of effective communication within the technical staff is another critical aspect we explored. Clear, continuous, and comprehensive communication channels among coaches, fitness trainers, and medical staff are essential to ensure that training programs are cohesively designed and dynamically adjusted based on real-time data. This collaborative approach enhances the decision-making process, enabling the development of training strategies that not only optimize performance but also mitigate injury risks.

Our work further elucidates the theoretical underpinnings of soccer training, providing a practical roadmap for implementing monitoring processes that inform training prescriptions. We included practical examples to bridge the gap between theory and application, offering fitness coaches and sports scientists tangible strategies to refine their practice. By addressing key questions concerning TL monitoring and the operationalization of IL and EL indicators, our framework equips practitioners with the tools necessary for an informed decision-making process.

In conclusion, the relationship between TL, physical performance, and injury prevention is complex and multifaceted, necessitating a well-defined conceptual framework to guide practice. Our contribution to this ongoing discourse offers a foundational understanding that supports the development of more sophisticated and effective training protocols. By integrating theoretical insights with practical applications, we aim to advance the field of soccer science, fostering a more cohesive and informed approach to training prescription and performance optimization.

Chapter III – The relationship between Training Load and Training Outcomes in soccer: a Machine learning approach

3.0 Overview

In the last decade, scientific community has shown interest on the complex relationship between training load and training outcomes. Several studies have investigated these phenomena through classical statistical approach reporting association between training load and training outcomes. For example, external load has been related to physical performance improvement as well as associated with injury risk. Unfortunately, given the multifactorial nature of physical performance and injuries, traditional statistical approach results as inappropriate to establish any relationship. Moreover, the huge amount of data produced daily by performance monitoring devices requires more sophisticated analysis than traditional statistics in order to properly obtain the optimal outcomes. Accordingly, the development of artificial intelligence and machine learning approach allowed the application of a multidimensional analysis providing useful insight when study the implication of training load and training outcomes. Indeed, preliminary, and promising studies have predicted injury, internal load, wellness and recovery through machine learning approach. It is worth noting that, although good predictions accuracy was found, the cause-effect relationship cannot be simply established when considering multifactorial phenomena. Worth noting, although association and relation between variables such as external load indicators or Acute Chronic Workload Ratio (ACWR) and injury has been found, the cause effect relation cannot be attributed (association and correlation do not imply causation). Despite the effort carried out by several studies that have applied artificial intelligence, this thesis considered the application of machine learning to delve into the study of physical performance, training load, recovery capacity and injury risk reduction. Specifically, literature provided a weak contribution concerning the association between match-related physical activity profiles and playing positions in different tasks considering a machine learning approach. Accordingly, we will apply a machine learning approach to profiling the playing position during different drills including official match from external load data. This approach will support practitioners to assess the physical impact of different drills (matches, SSGs, and MBEs) for different players' playing positions. Specifically, through this approach it will be possible to define the intensity of a soccer exercise by indicating whether a stimulus is predominantly neuromuscular or metabolic also by playing position offering valuable insight for practitioners during the training prescription process.

In the same way, the recovery ability has been often studied following a linear statistical approach (i.e., linear correlation) leading a limited and appropriate conceptual method. Indeed, the player's recovery ability can be influenced by multi-factors such as training load, fitness status, wellness (e.g., muscle soreness, sleep quality, stress and mood) as well as the acute and chronic fatigue. Accordingly, we will report a more proper approach (i.e., machine learning) to investigate the relationship between training load and recovery.

We will also provide the application of new load and performance score to investigate the microcycle training load through a machine learning approach. Indeed, given the huge amount of external load indicators that may be too specific and complex among coaches, the use of a summary indicator can help to obtain an overview of both the total load and the intensity in order to easily compare both players and training sessions.

At the end of this section, we will report a review with conceptual framework on non-contact injury prevention strategies applying the data informed approach aiming to understand if the exclusive implementation of “data” can be appropriate to this propose.

List of publications/projects discussed within Chapter III:

Guglielmo Pillitteri, Luca Petrigna, Salvatore Ficarra, Valerio Giustino, Ewan Thomas, Alessio Rossi, Filipe Manuel Clemente, Antonio Paoli, Marco Petrucci, Marianna Bellafiore, Antonio Palma and Giuseppe Battaglia - Relationship between external and internal load indicators and injury using machine learning in professional soccer: a systematic review and meta-analysis (2024) - Research in Sports Medicine – doi: 10.1080/15438627.2023.2297190

Guglielmo Pillitteri, Alessio Rossi, Paolo Cintia, Athos Trecroci, Marco Petrucci, Giuseppe Battaglia – Association between match-related physical activity profiles and playing positions in different tasks: a data driven approach (2024) - Journal of Sports Sciences – doi:10.1080/02640414.2024.2338026

Guglielmo Pillitteri, Alessio Rossi, Tindaro Bongiovanni, Giuseppe Puleo, Marco Petrucci, Giuseppe Battaglia - Elite Soccer Players' Weekly Workload Assessment Through a New Training Load and Performance Score (2024) – Research Quarterly for Exercise and Sport - doi: 10.1080/02701367.2024.2358956

Guglielmo Pillitteri, Rabi Muazu Musab, Filipe Manuel Clemente, Tindaro Bongiovanni, Marco Petrucci, Antonino Bianco, Marco Beato and Giuseppe Battaglia - Machine Learning Analysis of Intensity Profiles and Key Indicators in Standard Microcycle of Professional Soccer Players

Association between internal load responses and recovery ability in U19 professional soccer players: A machine learning approach (2023) – Heliyon - doi: 10.1016/j.heliyon.2023.e15454

Guglielmo Pillitteri, Rashid Bakirov, Filipe Manuel Clemente, Hugo Sarmiento, Marco Beato, Tindaro Bongiovanni, Clara Gabrielli, Marco Petrucci, Antonino Bianco, Giuseppe Battaglia - Machine Learning-Driven Injury Risk Assessment in Soccer: analysing Workload Dynamics and Predictive Modelling Approaches

Guglielmo Pillitteri, Filipe Manuel Clemente, Marco Petrucci, Hugo Sarmiento, Antonio Figueiredo, Tindaro Bongiovanni, Antonino Bianco, Giuseppe Battaglia, Tim J. Gabbett - A New Conceptual Framework Explaining Hamstring Injuries In Soccer – How Do The Data-Informed Approach Support Practitioners In Protecting Players? A Brief Review – Biology of Sports

3.1 Relationship between external and internal load indicators and injury using machine learning in professional soccer: a systematic review and meta-analysis

Pillitteri G, Petrigna L, Ficarra S, Giustino V, Thomas E, Rossi A, Clemente FM, Paoli A, Petrucci M, Bellafiore M, Palma A, Battaglia G. (2024). Relationship between external and internal load indicators and injury using machine learning in professional soccer: a systematic review and meta-analysis. *Res Sports Med.* 2024 Nov-Dec;32(6):902-938.

INTRODUCTION

Soccer is an intermittent and open skills team sports that requires high physical performance characteristics to support the fundamental technical-tactical aspects of the performance (280). Training allows athletes to improve their performance minimizing their Injury Risk (IR) through the variation in training stimulus (281). Inappropriate training stimuli and recovery could result in a deterioration in fitness level or in an increase in IR (282, 283). The high incidence of injury in professional soccer players could be the result of the wrongly modulation of training workload. Hence, the attention in players' recovery status as the season goes by should be widely considered by the medical and technical staff during the training scheduling process (27).

Training Load (TL) is defined as “a higher-order construct reflecting the amount of physical training that is actually done and experienced by the athletes” (4, 157, 284). Two dimensions called internal (IL), and external (EL) training loads characterize the TL (4, 158). Commonly, training prescription describes a short to long plan of the EL that permits to organize the exercises/training sessions (4, 157). The EL induces internal responses that reflect psychological, physiological, biochemical, metabolic, and biomechanical stress stimuli (57, 158, 159).

The acute dose–response paradigm indicates that specific internal responses, which are obtained by HR or RPE, are induced by prescribed external training factors (57, 285). Hence, monitoring EL and IL is essential for the management of athletes during both training and competition to maximize the athletic performance and minimizing injuries (283, 285). Specifically, it is suggested that the internal responses to a given EL should be taken into consideration since it may be observed different internal responses as a consequence of the same EL among different athletes (4). Indeed, several studies have examined the relationship between EL and IL to monitor training or competition load in, soccer (282, 285-300).

Some researchers (197, 214, 215, 301, 302) have investigated the application of a new index accounting for both the IL and EL to better understand the role of TL and its implication in performance and sport injuries prevention in soccer (303-307). For example, Suarez-Arrones et al. (2015) detected a lower overall running performance during match play at lower efficiency index scores (mean speed in $\text{m}\cdot\text{min}^{-1}$ /mean exercise intensity (%HRmax)) (214). In recent years, more complex and potentially more efficient analysis methods have been implemented to manage the huge quantity of data derived from the monitoring of the TL (308, 309). Machine learning (ML), which involves creating systems that learn or improve performance based on multidimensional data could allow practitioners to understand the complex relationships between phenomena with the aim of predictions (282). In fact, several studies used this analytical approach to predict IR and performance in team sports (309-311). ML includes different complex methods to manage a very large database to find relationships between multiple variable features. Therefore, it is necessary to apply pre-processing methods (e.g., imputation, standardization, and discretization) and to reduce the size of the data by selecting the most relevant features to avoid multicollinearity problem. Finally, well-performing models provide an idea of the most important factors, looking at which of them have the greatest influence in the decision-making process of the ML models. In this context, a growing number of studies have focused on the prediction of both injuries and performance through ML approach (16, 312, 313). Although a precious review reported that there is no consensus regarding the best way to predict sports injuries and performance via ML, each method is able to predict a specific variables in different contexts (314) such as Decision Tree (310) and Artificial Neural Network (308).

In the recent years, a growing number of investigations have focused on a better understanding the relationship between IL and EL in professional soccer players through the implementation of new indexes and ML approaches with the aim of TL monitoring and injury prediction. To the best of our knowledge, no systematic reviews critically summarize and evaluate findings regarding this topic. Hence, this systematic review and meta-analysis aims to study on one side the interaction between IL

and EL indicators, and, on the other side finding the relationship between TL indicators (both IL and EL) and injuries by using ML approaches in professional soccer players.

MATERIALS AND METHODS

This systematic review with meta-analysis followed the PRISMA 2020 guidelines.

Protocol and registration

The protocol of this systematic review was registered in PROSPERO (CRD42021245312) at 04/05/2021.

Eligibility criteria

Studies published in peer-reviewed journals, including those with the status of “in press” or “ahead-of-print”, were considered. Limitations to publications between 2010 and 2021 were established as machine learning studies applied to soccer have increased over the past decade. The limitation of the language to English as it has been used by most of the Impact Factor journals. The eligibility criteria were established based on the PECOS approach (population, exposure, comparator, outcome, study design): (i) population: participants were professional male football/soccer players with the age above 12 years old; (ii) exposure: players exposed at least 2 sessions, exercises, or competitions with an objective evaluation of both IL and EL parameters (iii) comparator: no comparison was planned to add in this review; (iv) Outcome(s): studies that correlated TL (both EL and IL) to non-contact injuries or research that applied ML approaches to predict TL and non-contact injuries. The main load indicators extracted have included internal (RPE, S-RPE, HR) and external (GPS variables related to distance, speed, acceleration and energy profile thresholds); Relationship between external and internal load through index, ratio and formula; machine learning indicators have included performance measures, predictive performance of machine learning methods, measure of feature importance, relevant predictors, outcome variable, predictor variable, data pre-processing, features selection, machine learning classification methods; (v) study design: observational studies. Exclusion criteria were: (1) studies that did not report any surrounding indicators of EL or IL in terms of volume and intensity; (2) studies in which there was no focus on the relationship between EL and IL, between TL and changes in performance or between TL and non-contact injuries; (3) studies investigated the effects of rehabilitation, nutritional strategies or environmental factors (e.g. heat, altitude); (4) studies that used biological markers as parameters to measure IL; (5) studies that did not use GPS-provided data to determine the EL; (6) studies that did not integrate both EL and IL to determine the TL; (7) studies where monitored training protocols referred to strength training; (8) if studies were reviews, meta-analyzes, abstracts, statements, opinion pieces, citations from scientific

conferences, commentaries, editorials, book reviews, books, letters and non-peer reviewed journal articles.

Information sources

The following databases were used to conduct the searches: PubMed, Scopus, and Web of Science. The screening was performed between 30 March 2021 and 15 May 2021. In addition, to automatic search, manual search to reference list of manuscripts were conducted by two authors. Moreover, experts were asked to help in the double-check of references.

Literature search strategy

The combinations of two groups of keywords were used. In detail, group 1 comprises: “training load”, “rpe”, “gps”, “internal external load”; group 2 comprises: “soccer”, “football”, “machine learning”, “injury”, “index”. The terms of group 1 and 2 were combined with AND. The references of the included studies were also checked to ensure to identify of all the relevant articles for this topic (Table 5).

Study selection

To select relevant articles, duplicates were removed. Afterwards, titles, abstracts, and full texts of the studies were independently screened against the inclusion and exclusion criteria by two authors (G.P. and S.F.). Any disagreements were discussed between the two authors and were resolved.

Data items

The following information were collected from the included studies:

Main outcomes: session-RPE or RPE (score obtained from the players); total distance and player load were adopted for meta-analysis.

The selected articles were classified according to their methodological quality aiming to understand the the interaction between IL and EL indicators, finding the relationship between TL indicators (both IL and EL) and injuries. Moreover, we sought the implication of TL to predict injuries by using ML approaches.

Information about the age, country of origin, competitive level, body mass, height, duration of the intervention, number of total observation and number of observations per athlete, individual observations were included were the context-related information analyzed by the studies.

information about the first author and year of publication; the main load measures extracted included internal (RPE, S-RPE, HR) and external (GPS variables) devices and parameters; relationship between external and internal load were sought through index, ratio and formula; machine learning indicators included performance measures, predictive performance of machine learning methods, measure of feature importance, relevant predictors, outcome variable, predictor variable, data pre-processing, features selection, machine learning classification methods were the methodological-related information were extracted from the studies. All data were summarized using descriptive tables and analyzed through a narrative synthesis.

Quality assessment

The quality of the included studies was assessed by two reviewers, and they resolved any disagreements about each item through deliberation. An adjusted version of Downs and Black checklist (315, 316) was applied to evaluate the quality of included studies using the following sub-scale: reporting (items, 1, 2, 3, 5, 6, 7, and 10), external validity (items 11 and 12), internal validity-bias (items (15,16,18, and 20), internal validity-confounding (items 21 and 25), and power (item 27). The score of the item 27 was modified from 0-5 to 1 or 0 so that a study received 1 if the study had an appropriate power, in other aspect, it was scored 0. Kappa correlation coefficient was used to detect Inter-Rater reliability for each checklist item between the two reviewers. Studies with scores of 11 or higher (65%) were at a low risk of bias, and investigations with scored below 11 were at a high risk of bias.

Meta-Analysis

To conduct a meta-analysis the “metafor” package of the R software (Version 1.4.1103), using the Hunter-Schmidt model on raw correlation coefficients (bias corrected) between S-RPE and TD, as well as S-RPE and PL, was adopted. This approach reduces estimator variance when correlations from each study do not need to be transformed into z-scores (317). Significance was set at $p < 0.05$. The effect size was represented through a forest plot with 95% confidence interval (CI). A funnel plot was also performed to understand publication bias. Heterogeneity was explored using the I^2 statistic, in which values $< 50\%$ indicate low heterogeneity, $50\text{--}75\%$ moderate heterogeneity, and $> 75\%$ high heterogeneity. Since both models presented heterogeneity below 50%, no moderator analysis was conducted.

RESULTS

A total of 35310 articles were retrieved through the database searches of which 15342 were duplicates. Twenty-five studies met the inclusion criteria and were included in the review: twenty-two were included after screening the titles, abstracts, and full texts; three were identified through the references screening of all the included studies. The flow diagram (Fig. 3) summarizes the screening process. All the included studies used GPS and/or triaxial accelerometers variables to assess EL. Eleven articles addressed the relationship between EL and IL of which nine used RPE and or S-RPE for monitoring IL and two used both HR and S-RPE indicators. Five articles used EL/IL new indexes: four applied HR and one used RPE and S-RPE, for IL assessment. Five studies predicted IL indicators. In particular, two predicted HR, while three predicted RPE through EL applying ML approaches. Three studies investigated the association between EL (GPS) and IL (RPE) with IR. Only one study predicted IR (311) implementing ML approaches through IL and EL.

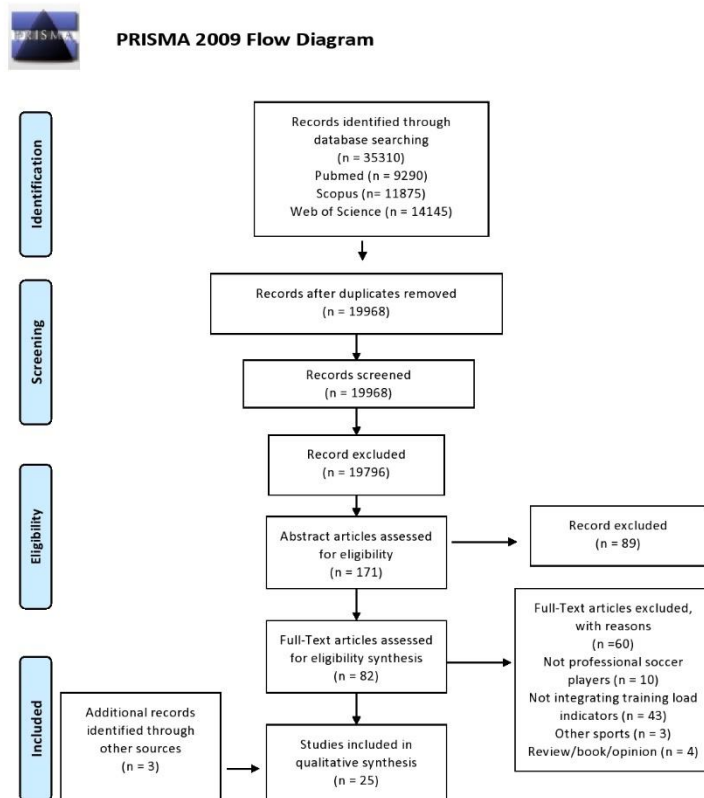


Fig.3 Prisma 2009 Fow Diagram

Overview of the studies

Table 3 shows the main characteristics of the included studies. Table 3.1 shows TL indicators (external and internal), and new-derived indexes or ratios.

Sample size varied between 10 and 48 athletes (total 636 individuals). Participants were professional male soccer players (mean age 24.3 ± 3.3 years, height 180.8 ± 2.2 cm, weight 75.1 ± 2.9 kg) of studies carried out in Australia, Austria, Belgium, Brazil, France, Italy, Netherlands, Norway, Portugal, Russia, Spain. The studies research protocol duration varies between 6 weeks and 2 seasons. IL was assessed with RPE proposed by Foster [119, 120], S-RPE (derived multiplying RPE x duration) [119, 120], and/or HR, while EL using GPS [54] and/or accelerometer indicators. Twenty-one studies (84%) used standard statistical analysis (85, 175-178, 197, 214, 215, 301, 302, 318-328) and only four (16%) (16, 311-313) used ML approaches to analyse the data. Only four studies regarding injuries were included: three used IL and EL to understand their association with injuries (320, 322, 323), and one used ML approach to predict IR (311).

ML studies characteristics and results are presented in Table 3.2 and 3.3, respectively.

Table 3. Main Characteristics of the Studies included in the review

Studies Author, year	Sample number / level / age (years) / mass (kg) / height (cm)	Duration	Obs. sample Obs. per athlete/tot. individual obs.	Findings
Enes, 2021	23/First division $26.7 \pm 3.9 / 78.0 \pm 5.0 / 178.0 \pm 5.2$	38 weeks		Physical measures and EL influenced on match-based IL and can be used for IL prediction.
Gaudino, 2015	22/Professional $26 \pm 6 / 79 \pm 7 / 182 \pm 7$	38 weeks	Median observation per players was 86 ± 28 (range 25–120) 1892 individual training observation mean duration of 57 ± 16	RPE of TL was correlated with HSR distance and the number of impacts.
Geurkink, 2019	46/elite 25.6 ± 4.2	June 2015 and March 2017	913 individual training observations/61 training sessions	ELIs are the strongest predictors of the S-RPE.
Gomez-Piriz, 2011	22/first division $26.74 \pm 4.2 / 179.74 \pm 4.0 / 73.7 \pm 3.3$	February to March 2008	124 data were obtained and analysed	TBL is a valid tool to determine specific-soccer TL.
Grunbichler, 2020	14/Austrian Second League/ $22.6 \pm 4.3 / 181.5 \pm 5.7 / 75.7 \pm 5.8$	13-week period (competitive season) 2017/2018 from March 2018 until June 2018	514 individuals training and 180 match observations/44 training sessions and 16 competitive matches	TL recorded during the days before a match can predict match workload efficiency.
Jasper, 2018	38/highest league in the Netherlands/ $22.7 \pm 3.4 / 1.83 \pm 0.06 / 77.0 \pm 6.7$	two seasons (2014/2015 and 2015/2016)	23 players: (35 to 160) mean and st. dev. of 125 ± 34 sess. 28 players: (51 to 163) mean and st. dev. of 109 ± 33 sess.	ML can predict RPE based on a large set of ELIs.
Jasper, 2018	35/first team at the highest level (Eredivisie)/ $23.2 \pm 3.7 / 77.5 \pm 7.4 / 1.82 \pm 0.06$ m,	two seasons (2014/2015 and 2015/2016)	external load data for field training sessions and matches was 870 of 8103 (11%)	ELIs are associated with increased or decreased IR. Cumulative weekly loads for TD DECEff is recommended. A high ACWR for THSR should be avoided. Protective effects were found with medium ACWR for ACCEff, DECEff, and S-RPE
Lacome, 2018	10/elite French football team/ $26 \pm 5 / 76 \pm 5 / 182 \pm 6$	one season (2016/2017)		Large associations between the HR responses to SSGs and some SSGs.

Malone, 2018	37/(Liga Nos, Portugal) /25 ± 3/183 ± 7/72 ± 7	48 weeks 2015/2016	22080 individual pitch-based training sessions / 460 training sessions	Workload measures were associated with measures and IR. Cumulative HSR and SR workloads or large week-to-week changes in these workloads increased IR. Players exposed to large and rapid increases in HSR and SR distances were more likely to sustain a lower limb injury.
Malone, 2018	48/(Liga NOS and Champions league)/25.3 ± 3.1/183 ± 7/72 ± 7	2014/2015 season	22080 individual pitch-based training sessions / 460 training sessions	Wellbeing measures were related with reduction in training measures.
Marynowicz, 2020	18/youth national teams/17.81±0.96/179.47 ± 4.77/70.94 ± 4.72	2018/2019 in-season competition (18 weeks)		S-RPE and related to many EL factors, allows the monitoring of both acute load and cumulative load.
Maughan, 2021	20/17.4 ± 1.3/178.0 ± 8.1/71.8 ± 7.2	46-week (6-week pre-season and 2 competitive phases) (20-weeks and 19-weeks) split by a 2-week break	total of 3221 sets of observations	There are strong correlations between S-RPE, S-RPE-L, S-RPE-B, and EL variables.
Maughan, 2020	20/17.4 ± 1.3/178.0 ± 8.1/71.8 ± 7.2	2018/2019 season	2827 individual recordings comprising of 696 MD recordings and 2131 training session	TD, PL and LI.Running showed large to very-large correlations with S-RPE. HSR showed small to large correlations, SD showed trivial to moderate correlations. ACC showed moderate correlations, whilst DEC showed small to large correlations with S-RPE.
Montini, 2020	20/Italian (Serie A) 25.8 ± 4.1/76.8 ± 4.3/184 ± 4.6	October 2016 to August 2017	In-season period (34 training sessions and matches (October 2016 and December 2016); the pre-season (30 training sessions and matches (July and August 2017))	S-RPE and kJ as the most effective TL indicators in soccer.
Rago, 2019	13/Italy (Serie Bwin.it)/25.8 ± 3.5/181.5 ± 5.6/78.3 ± 5.9	2016/2017 season	256 individual observations/ a median of 20 training sessions per player (range: 15–25 sess.)	The magnitude of the relationships between EL and RPE parameters appear to slightly strengthen when EL are adjusted to individual fitness capacities, with special emphasis on cardiorespiratory fitness.
Rossi, 2019	22/Italian championship/21.9 ± 4.5/180.6 ± 5.2/72.3 ± 4.1	2016/2017 season	1674 individual sessions/ 195 collective sessions	ML approach permits to reveal the IL based on external and contextual features. RPE is affected by the workload performed in the previous training week, while S-RPE reflects the workload performed in the current training session.
Scott, 2013	15/Australian A-League/24.9 ± 5.4/77.6 ± 7.5/181.1 ± 6.9	2010/2011	97 individual sessions	TD, LSA volume, and PL are adequate indicators of EL during field-based compared with measures of IL. HSR and VHSR volume are somewhat related to IL.
Silva, 2018	20/Russian Premier League and in the UEFA Champions League/26.53 ± 3.92/182.88 ± 5.52/76.69 ± 6.14	2015-2016 second pre-season period	270 individual training obs.	TRIMP method and EL and time HR 80% (THR80%) as the best HR indices of TL and intensity, respectively. ACC and HIRE (high intensity bursts) were the physical activities that were most impacting in HR responses.
Suarez-Arrones, 2015	30/Champions League or UEFA Europa League	two seasons	(n =348)/ 4-15 times on each player over a period of two seasons	Physical and physiological demands of professional soccer players showed several differences among playing positions.
Torreno, 2016	26/national league, national cup, national super cup and UEFA Europa League/27.3 ± 3.4/180.4 ± 3.6/76.2 ± 6.8	two seasons	(n = 223 match files)/ 3-15 times on each player over a period of two seasons	The relationship between EL and IL measures among position-specific confirms that players with more overall running performance during the full-match (W-MD and 2ndS) presented the higher values in Effindex.
Vallance, 2020	40/French Ligue 2/29.4 ± 5.8/175.3 ± 5.2/76.5 ± 8.2	one full-season (2017/2018) June 2017 to May 2018	245 training sessions	The subjective variables (i.e., IL) of the pre-session questionnaire (such as sleep quality, fatigue, shape, mood) as well as post-session questionnaire (satisfaction and pleasure) and RPE are found to be determining factors in the occurrence of injuries.
Wiig, 2020	18/Norwegian Premier league 26/183/80	In-season March to November (32 weeks)	207 individual training obs/ 21 training sess. median of 10 (4) obs. per player (range 7–18)	The EL variables with no threshold or low intensity-threshold had the strongest relationships with S-RPE.
Derbidge, 2020	10/professional development league/19.6 ± 1.4/74.4 ± 8.7/180.5 ± 5.3	2018/2019 8-week period during the in-season	7 training sessions	The significant effect observed between PW and TD:HRe, PL:HRe and ED:HRe during the SSG's allow scope for external:internal (E:I) ratio's to be used as a 'invisible' fatigue detection tool.

		competitive phase		E:I ratios is not an appropriate method to determine neuromuscular fatigue.
Lu, 2017	45/Australian A-League and Asian Champions League/26.4±5.1/181.3±7.1/74.5±12.1	2013/2014 (14 weeks preseason and 32 weeks in season) and 2014/2015 (14 weeks preseason and 31 weeks in season)	211±55 sessions per participant	High absolute and relative load of both exposure and S-RPE workload sustained determined injuries. The absence of any 'spike' in workload prior to injury occurrence was reflected in the lack of week-to-week changes and monotonous profile. Exposure and S-RPE workload ACWR tended to be the highest in comparison to the other load variables.
Alemdaroğlu, 2020	20/professional soccer team/27.6/177.6±7.1/69± 8.3	10-week soccer season	761 individual field-based training	S-RPE and both HR-based TL models show strong correlations with the number of ACC and DEC actions and with TD, correlations with distances covered in high-speed zones are less convincing.

Legend: EL, external load; IL, internal load; RPE, rating of perceived exertion; TL, Training Load; HSR, High Speed Running; ELIs, External Load indicators S-RPE, Session-Rate of Perceived Exertion; TBL, Total Body Load; ML, Machine learning; IR, injury risk; TD, Total Distance; DECEff, Deceleration Effort; ACWR, Acute Chronic Workload Ratio; THSR, total high-speed running; ACCeff, Acceleration Effort; HR, heart rate; SSG, Small Side Games; GPS, global positioning system; HRA, delta heart rate; HSR, high speed running; SR, sprint running; S-RPE-L, Session-Rate of Perceived Exertion-leg muscle exertion; S-RPE-B, Session-Rate of Perceived Exertion-breathlessness; PL, PlayerLoad and LIRunning, low intensity running; SD, sprint distance; LSA, low speed activity; VHSR, very high speed running; HIRE, high intensity repeated efforts; 2ndS, second strikers; PW, perceived wellness; HRe, HR exertion; ED, equivalent distance; ACC, accelerations; DEC, decelerations;

Table 3.1 Main Features of the Studies

Studies Author, year	Measures of load		Relationship/index External/internal load ratio
	Internal Device/parameters	External Device/parameters	
Enes, 2021	Session-RPE Borg CR-10 scale were multiplied by the time (in minutes) and expressed in arbitrary units (a.u.)	GPS device (OPTIMEYE S5, Catapult®, Melbourne, Australia) Player Load (au), Player Load min-1 (au), Total Distance (m), Relative Distance (m.min-1), Distance >20 km.h-1 (m), Quantity of Stimuli >20 km.h-1 (frequency), Maximal speed (km.h-1).	No
Gaudino, 2015	RPE training load (RPE-TL) Borg CR-10 scale were multiplied by the time (in minutes)	10-Hz GPS integrated with a 100-Hz 3-dimensional accelerometer, a 3-dimensional gyroscope, and a 3-dimensional digital compass (STATSports Viper, Northern Ireland). Total distance (m), high-speed distance (m), very-high-speed distance (m), very-high-speed runs (n), impacts (n), dynamic-stress load (AU), accelerations (n), decelerations (n), energy expenditure (kcal), high-metabolic-power dist.(m)	No
Geurkink, 2018	RPE scale Borg CR-10 20 Hz portable HR monitors (Polar Team Pro, Kempele, Finland 10) HR-zones relative to their maximum HR (50% - 60%, 60% - 70%, 70% - 80%, 80% - 90%, 90% - 100%) Time spent in each HR-zone relative to the total time spent in the 5 HR-zones EDW TRIMP	GPS 10 Hz (Polar Team Pro, Kempele, Finland 10 with incorporated accelerometers of 100 Hz Total distance (m), Total time (s), Total number of sprints (n), Deviation of total distance, Diff. in total dist. between players during a training sess., Deviation of total sprints, Diff. in the total number of sprints between players during a training sess. Average speed, distance covered in 5 speed zones (km/h) (3.00 - 6.99, 7.00 - 10.99, 11.00 - 14.99, 15.00 - 18.99, > 19.00), normalized proportion of distance covered in each speed zone, number of acc. in each zone (m/s2) (0.50 - 0.99, 1.00 - 1.99, 2.00 - 2.99, 3.00 - 50.00), number of dec. (m/s2) (0.50 - 0.99, 1.00 - 1.99, 2.00 - 2.99, 3.00 - 50.00), normalized proportion of number of acc. and dec. in each zone, differences in training duration between players during a training sess.	No
Gomez-Piriz, 2011	session-RPE (21-point scale)	GPS tracking device (SPI Elite; GPSports Systems) 1Hz Body load: Computation of player body load during exercise involved the use of the next acceleration zone forces provided in "g" force by the accelerometer of the GPS:	No
Grunbichler, 2020	Polar Team Pro System (Polar Electro Oy, Kempele, Finland). 200 Hz movement sensors as well as heart rate sensors duration (min), Polar Modified training impulse (TRIMPMOD)	Polar Team Pro System (Polar Electro Oy, Kempele, Finland) 10 Hz global positioning (GPS) Duration (min), total distance (m), equivalent distance (m), high speed running (> 14.4 km/h) dist. (m), very high speed (> 19.8 km/h) running dist. (m), sprinting (> 25.2 km/h) dist. (m), number of medium (2.00 - 2.99 m/s2) and high (> 3.0 m/s2) acc. number of medium (-2.00 - -2.99 m/s2) and high (< -3.0 m/s2) dec.	new index= workload efficiency (ratio of external and internal load in a match.); ED/TRIMPMOD
Jasper, 2018	RPE (modified Borg CR-10 scale)	10 Hz GPS and 100 Hz accelerometer technology (Optimeye S5, Catapult Sports, Melbourne).	

Jasper, 2018	RPE Borg CR-10 scale. The load arbitrary units (AU): RPE x training or match duration.	Speed (8 ELIs), Acc. and dec. (18 ELIs), PlayerLoad (10 ELIs), RHIE (13 ELIs) 10 Hz GPS technology (Minimax S4 and Optimeye S5, Catapult Sports, Melbourne, Australia). Total distance covered (TD), distance covered at high speed (THSR; >20 km h ⁻¹), N° (ACCeff) >1 m s ⁻² , N° (DECeff) <-1 m s ⁻²	ACWR ^b
Lacome, 2018	Heart rate: Polar H1 units (Polar, Kempele, Finland)	5-Hz GPS and 100 Hz accelerometers (SPI-Pro, Team AMS R1 2016.8, GPSport, Canberra, Australia) Total distance (TD, m), high-speed distance (HS, above 14.4 km.h-1, m), very-high speed distance (VHS, above 19.8 km.h-1, m), velocity and force load (vL and fL respectively, a.u) mechanical work (MechW, a.u)	HRA (i.e, the difference between the predicted and actual HR)
Malone, 2018	Borg CR-10 rate of perceived exertion (RPE) scale. RPE was multiplied by the session duration to generate an RPE-load	10-Hz GPS unit (STATSports Viper, Northern Ireland). High-speed (>14.4 km·h-1), sprint (>19.8 km·h-1) running distances	Chronic training loads ^c acute:chronic workload ratio ^d
Malone, 2018	Borg CR-10 rate of perceived exertion (RPE) scale. RPE was multiplied by the session duration to generate an RPE-load	Global positioning technology device, with tri-axial accelerometers (MinimaxX, Team 2.5, Catapult Innovations, Australia). Tot. dist. (m), Tot. high-speed dist. (≥19.8 – 25.2 km·h-1), sprint dist. (≥ 25.2 km·h-1), max vel. (km·h-1), max vel. Dist. (m), max vel. exposures (n), player load (AU), player load slow (AU)	Total Distance:RPE (m·min-1) Total High Speed Distance:RPE (m·min-1) Player Load:RPE (AU·min-1) PlayerLoadslow:RPE (AU·min-1)
Marynowicz, 2020	RPE: CR-10 Borg scale The sRPE was calculated by multiplying training duration (minutes)	10 Hz GPS, integrated with a 400 Hz triaxial accelerometer, and a 10 Hz triaxial magnetometer (PLAYERTEK, Catapult Innovations, Melbourne, Australia) Duration (min), Distance (m), PlayerLoad (a.u), High-speed running dist. (m), Impacts (n), Dist. in dec. (m), Dist. in acc. (m), Acc. (n), Dec. (n), Dist. (m) per min., PlayerLoad (a.u) per min., Impacts (n) per min., High-speed running dist. (m) per min., Dist. in dec. (m) per min., Dist. in acc. (m) per min., Acc. (n) per min., Dec. (n) per min.	
Maughan, 2021	RPE: (Borg CR10). Each RPE score was multiplied by session duration to calculate session loads	10Hz GPS units (Optimeye X4, Catapult Sports, Melbourne, Australia, Firmware version 7.27)/triaxial accelerometer 100Hz Tot. dist. (TD, m), PlayerLoadTM (PL, au), low intensity running (LIR, < 14.4km.h-1, m), running (HIR, 19.8 24. 98km.h-1, m), sprint (SPR, > 24. 98km.h-1, m), acc. (>2m.s-2 count), dec. (<-2m. s 2, count) expressed in their absolute units and per min.	
Maughan, 2020	RPE: RPE score was multiplied by session duration to obtain subjective training load	10Hz GPS units (Optimeye X4, Catapult Sports, Melbourne, Australia, Firmware version 7.27)/triaxial accelerometer 100Hz Tot. dist. (m), PlayerLoad (au), low intensity running (< 14.4 km.h-1, m), running (19.8 - 24.98 km.h-1, m), sprinting (> 24.98 km.h-1, m), acc. (>2 m.s-2 count); and dec. (<-2 m.s-2, count)	
Montini, 2020	RPE: CR-10 scale Session rating of perceived exertion values were obtained by multiplying the value of the 10-point Borg scale and the training duration in minutes	GPS device (20 Hz GPS system; GPEXE, Exelio Srl, Udine, Italy) operating at a sampling frequency of 18.18 Hz. Total energy expenditure was expressed in kJ·kg21. Such parameter represents the total external training load	Individual index between ITL and ETL parameters.
Rago, 2019	RPE using Borg's category ratio scale (CR10) The overall training load was calculated by using session-RPE (s-RPE), that is calculated multiplying the RPE score (in arbitrary units) by the individual training duration (in min)	10-Hz GPS units (BT-Q1000 Ex, QStarz, Taipei, Taiwan). moderate-speed running (MSR), high-speed running (HSR), sprinting, Total high-intensity activity (THIA) was given by the sum of MSR, HSR and sprinting.	
Rossi, 2019	RPE: CR-10 Borg scale. The RPE is multiplied to the duration of the training session to obtain the training load (S-RPE).	10 Hz global position system (GPS) (Playertek, Dundalk, Ireland) that is also characterized by a 400 Hz Tri-Axial Accelerometer and 10 Hz Tri-Axial magnetometers 21 kinematic velocity, 37 metabolic metabolic power, 30 mechanicals	ACWR, (EWMA) ^c , Monotony Week ^f , Monotony Month ^g , StrainWeek ^h , Strain Month ⁱ , RPEPrevPlayer ^j , RPEPrevTeam ^k

			RPEPrevRole ^h ID training ^m
Scott, 2013	Polar Team2 Pro (Polar Electro, Kempele, Finland) (HRmax), (HRrest), Banister's TRIMP, Edwards' TRIMP Borg's Category Ratio-10 RPE scale sRPE score provided by players was multiplied by training duration (min)	MinimaxX 2.0 GPS device (Firmware version 6.59, Catapult Innovations, Scoresby, Australia) and triaxial accelerometer (Kionix: KXP94) Average speed (m/min), TD covered (m), Volume of low-speed activity (LSA; <14.4 km/h), high-speed running (HSR; >14.4 km/h), very-high-speed running (VHSR; >19.8 km/h) were recorded in meters and seconds, Player-load	
Silva, 2018	A heart rate monitor (Polar Electro Inc., Lake success, NY, USA) Hrmax VO2max tHR70 time spent HR above 70% of max tHR80 time spent HR above 80% of max tHR85 time spent HR above 85% of max HRE Heart rate exertion ETL (Edwards training load) TRIMP	10 Hz GPS integrated with a 100-Hz 3-dimensional accelerometer, a 3-dimensional gyroscope, a 3-dimensional digital compass and a heart rate receiver (Viper Pod, 50 gr, 88 x 33 mm, STATSports Viper, Northern Ireland). Acc. > 2 m/s ² (n), Acc. > 2.5 m/s ² (n), Acc. > 3 m/s ² (n), Dec. > 2 m/s ² (n), Dec.> 2.5 m/s ² (n) Dec. > 3 m/s ² (n), Tot. dist. (m), Dist. > 14.4 Km/h (m), Dist. 14.4 – 19.8 Km/h (m), Dist. > 19.8 Km/h (m), Impacts (n), Dynamic stress load (AU), Total loading (AU), High intensity bursts (n), High metabolic load dist. (m)	
Suarez-Arrones, 2015	Short-range telemetry (SPI-Pro--X, GPSports, Australia) (HRmax)	GPS unit (SPI Pro X; GPSports Systems, Canberra, Australia) 5 Hz and accelerometer data at 100 Hz respectively N° of Sprints, Average time of sprint (s), Average minutes between sprint, Average Sprint Distance, Maximal Sprint Distance, Maximal Speed, RSS (Repeated-Sprint Sequence), Relative total distance (RD) (m·min ⁻¹) ^a , Work-to-rest ratio (RD>7.0 km·h ⁻¹ / RD≤7.0 km·h ⁻¹)	The performance efficiency (Effindex) ^o
Torreno, 2016	HR: HR belts (Polar®, Finland) The data stored includes HR, time, speed, and distance.	GPS unit (SPI Pro X; GPSports Systems, Canberra, Australia) GPS 5 Hz frequency and accelerometer data to 100 Hz Tot. dist. covered (TD), distance covered running above moderate-speed (>13.0 km·h ⁻¹), above high-speed (>18.0 km·h ⁻¹).	The performance efficiency (Effindex)
Vallance, 2020	RPE (VAS10) rating of perceived exertion of the session	10 Hz GPS system (Optimeye S5, Catapult Innovations, Melbourne, Australia) integrated with a 100 Hz triaxial accelerometer and a gyroscope. tot_dur., tot_dist., total Player Load, vel ^p : max_vel maximum speed in m/s	
Wiig, 2020	Borg CR- 10 scale sRPE-TL was calculated by multiplying the sRPE by the session duration in minutes	GPS: 10-Hz (OptimEye S5, Firmware 7.18; Catapult Sports, Melbourne, Australia) 100 Hz. 3-dimensional accelerometer, magnetometer, and gyroscope PlayerLoad, PlayerLoad2D, Total distance (m), (high intensity events) HIE > 1.5, HSRD(>14.4m/s), and VHSRD (>19.8 m/s), HIE > 2.5, and HIE > 3.5	
Derbidge, 2020	HR monitors (T31, Polar, Finland) A novel measure of HR exertion (HRe) ^q HR max	10Hz GPS unit integrated with a 100 Hz accelerometer (Viperpod, Statsports, Ireland) TD (m), PlayerLoadTM(PL) (au) and Explosive distance (ED) (is the cumulative distance an individual has spent accelerating and decelerating >2 m/s) (m)	E:I Ratio (au) = external load/internal load TD: HRe, PL: HRe ED: HRe
Lu, 2017	s-RPE (Borg's CR-10)	5 Hz GPS unit (10Hz interpolated to 15Hz) with a 100Hz, 16G triaxial accelerometer (SPI HPU GPSports, Canberra, Australia) Total distance (m), distance by speed zones (m), mean speed (m.s-1), and body load (Arbitrary units; AU), low speed running (<14. 4km.h-1 high speed running (>14. 5km.h-1), and very high-speed running (>20km.h-1)	Acute:Chronic Workload Ratio
Alemdaroğlu, 2020	RPE (CR-10 scale, table 1) by multiplying the training duration (in minutes) by the RPE Two HR-based methods: PLR TRIMP EDW TRIMP ^s	GPS (Polar electro, Kempele, Finland). Total distance (TD) was measured, with the players' activities divided into five speed thresholds ^r , Dec. and acc. (actions thresholds were set for low-intensity, moderate-intensity and high-intensity ACC actions at 1–2, 2–3, and >3 m.sn-2; DEC actions at -1–2, -2–3, and >-3 m.sn-2)	

Legend: a: 5–6g: light impact, hard acc., dec., or change of direction, 6–6.5g: light to moderate impact (player collision, contact with the ground), 6.5–7g: moderate to heavy impact. (tackle), 7–8 g: heavy impact (tackle), 8–10g: very heavy impact (scrum engagement, tackle); and 10+g: severe impact, tackle, or collision. b: Acute Chronic Workload Ratio (calculated weekly by dividing the 1-week load of the most recent week by the 4-week rolling average weekly load). These load variables were calculated for selected external and internal load indicators. c: averaged 21-day load, the absolute change in load from the previous week; d: comprised of a 3-day acute load period and a 21-day chronic load period; e: with span = 6/EWMA with span = 28) of the 88 daily features (i.e., 21 kinematic, 37 metabolic, and 30 mechanical); f: Reflection of training variation across a week (6 days). It is the ratio between training loads (i.e., product between duration and rate of perceived exertion (RPE)) mean performed in one week and its standard deviation; g: Reflection of training variation across a month (28 days). It is the ratio between training loads mean performed in one month and its standard deviation; h: Reflection of overall training stress from the week. It is the product between the training loads mean and the Monotony Week; i: Reflection of overall training stress from the week. It is the product between the training loads mean and the Monotony Month; j: Mean of the RPE provided by a player in the previous week (6 days) Win-Draw-Loss Results of previous match; k: Mean of the RPE provided by the team in the previous day; l: Mean of the RPE provided by the players with the same role in the previous day; m: Seven Boolean features reflect the day of the week when players perform a training was performed; n: RD: 0.1 – 7.0 km·h⁻¹ (m·min⁻¹), RD: 7.1 – 13.0 km·h⁻¹ (m·min⁻¹), RD:13.1 – 18.0 km·h⁻¹ (m·min⁻¹), RD:18.1 – 21.0 km·h⁻¹ (m·min⁻¹), RD: >21.0 km·h⁻¹ (m·min⁻¹), RD: >13 km·h⁻¹ (m·min⁻¹), RD: >18 km·h⁻¹ (m·min⁻¹); o: was calculated as [mean speed in m·min⁻¹/mean exercise intensity (%HRmax)]; p: B1 distance covered between 0 and 1 km/h, B2 distance covered between 0 and 6 km/h, B3 distance covered between 6 and 15 km/h, B4 distance covered between 15 and 20 km/h, B5 distance covered between 20 and 25 km/h, B6 distance covered at more than 25 km/h, acc_B2 number of accelerations above 2 m/s², acc_B3 number of decelerations above 2m/s²; q: HRe represents the total volume of cardiovascular exertion an individual will experience relative to time; r: walking (.1–7.1 km.h-1); jogging (jog) (7.2–14.3 km.h-1); running (run) (14.4–19.7 km.h- 1); high-speed running (HSR) (19.8–25.1 km.h-1); sprinting (>25.1 km.h-1); s: method, which determines TL by calculating the product of the accumulated training duration (minutes) in 5 HR zones applying a coefficient relative to each zone (50 – 60% of HRmax =1; 60 –70% of HRmax = 2; 70 – 80% of HRmax = 3; 80 –90% of HRmax =4; 90 –100% of HRmax = 5) and then summing the result.

Authors, year	Outcome Variable	Predictor Variable	Analysis procedures	Data pre-processing	Features selection	Machine Learning Classification Methods
Geurkink, 2019	Session Rate of Perceived Exertion (S-RPE)	GPS data: N° 70 External Load Indicators (ELIs) Internal Load Indicators (ILIs) Individual Characteristics (ICs) Supplementary Variables (SVs)	5-fold cross-validation, on average 50 and 13 training sessions were used in respectively the training and test set in each fold.	No	Gradient Boosting Machines, One-hot encoding, Loose accuracy approach	Generalized Additive Models, Multivariate Adaptive Regression Splines, Decision Tree, Random Forest, Linear Regression, Support Vector Regression
Jasper, 2018	RPE	GPS data: N° 67 External Load Indicators (ELIs)	Experiment 1: data from the first season served as the learning set and the data from the second season as the testing set; Experiment 2: Each season's data was subdivided temporally such that the first 75% served as the learning set and the last 25% served as the testing set	No	Least absolute shrinkage and selection operator (LASSO)	Artificial neural networks (ANN), (LASSO), Baseline
Rossi, 2019	RPE and Session Rate of Perceived Exertion (S-RPE) (observed and the predicted)	GPS data: N° 182 individual features and 11 contextual	The dataset was divided into 3 folds. For each fold, 90% of the dataset was used as a training set and 10% of it as a test set. Classifiers were validated on the remaining 80% of the dataset with a 3-fold stratified v cross-validation strategy, stratified by player identification (ID) Each sample in the dataset was tested once, using a model that was not fitted with that sample.	No	Recursive Feature Elimination with Cross-Validation (RFECV)	Decision Tree Regression (DT), Random Forest Regression (RF), Epsilon-Support Vector Regression (SVR), Logistic Regression (logit), K-Nearest Neighbors (KNN), Linear Decision Tree
Vallance, 2020	Injury at 1 week Injury at 1 month.	Personnal Features (n°5) GPS device: (n° 12) Pre-Session Questionnaire (n° 7)	Hyperparameters were tuned using a Bayesian optimisation procedure according to the different evaluation metrics. 10-fold cross-validations using 4 measures of predictive performance according to the two predictive	Data imputation: imputation by mean (for numerical variables)	No	K-Nearest Neighbours (KNN), Linear Discriminant Analysis (LDA),

		Post-Session Questionnaire (n° 3)	horizons previously mentioned (1 week and 1-month). This process was repeated 10 times to check the stability of the model's performances.	and frequency (for categorical variables) was performed upstream the model comparison was made.		Logistic Regression (logit), Ridge classifier (Ridge), Gaussian Naive Bayes classifier (GNB), Classification tree (tree), Random forest (forest), Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), eXtreme Gradient Boosting (XGB)

Table 3.3 Machine Learning: Study Results Characteristics				
Author, Year	Performance Measures	Predictive Performance of ML Methods	Measure of Feature Importance	Relevant Predictors
Geurkink, 2019	Accuracy: the mean absolute error (MAE) and Root Mean Squared Error (RMSE).	ELIs, since total distance, total time and number sprints are among the strongest predictors. Total duration and the number of sprints were also strong predictors	No	ELIs, since total distance, total time and number sprints are among the strongest predictors.
Jasper, 2018	Mean Absolute Error (MAE) was used to assess a model's predictive performance.	The LASSO model made more accurate predictions than the ANN model. The group models resulted in equivalent or even more accurate predictions of the reported RPE values than the individual models.	LASSO only selects a subset of the ELIs, those with a non-zero coefficient, to be included in the model.	Machine learning techniques are able to predict RPE based on a large set of ELIs. These techniques can be applied to support expert knowledge for the selection of key ELIs such as decelerations.
Rossi, 2019	Root Mean Squared Error (RMSE) Mean of Absolute Difference (MAD) Bland-Altman analysis	Decision Tree The ordinal regressor is the best classifier in describing both the players' RPE and S-RPE.	No	Predicted RPE and S-RPE are higher than the observed ones when players perceived low RPE while it is lower when the players perceived a high RPE. External loads reflect RPE and S-RPE. Inconsistent relationship between extreme values of RPE and training workload. The distance to the matchday affect the players 'perceived exertion. RPE and S-RPE are strongly affected by the volume of the total training and weakly affected by the training intensity.
Vallance, 2020	Accuracy Precision Recall Area Under the ROC Curve (AUC)	The best performances were obtained with the KNN, tree, forest and XGB classifiers. It is also noticeable that higher performance can be obtained for 1 month predictions with maximum values around 97% for all metrics. The different features related to satisfaction, pleasure and RPE appear to be the most	The features importance weights are calculated with two different approaches: CART impurity decrease which is available only for tree-based classifiers and features permutation scrambling sensitivity which can be computed on any predictive model.	For 1-week injury prediction, internal load features data were more accurate than external load features while for 1-month injury prediction, the best performances of classifiers were reached by combining internal and external load features.

		important in terms of precision and recall for 1-week injury prediction. Overall, pain and shape related features as well as personal features (age and weights) appear to be the most important features for accurate injury risk detection (i.e., to get high recall values) and pain; worry as well as fatigue and external load variables are important to get reliable 1-month injury prediction (i.e., with high precision values).		

Quality assessment

The methodological quality of the included studies was assessed according to Downs and Black checklist, which is presented in the supplementary section. 11 out of the 25 studies (44%) were selected as high-quality, while 14 (56%) as low-quality. K Inter-Rater reliability agreement was 0.659 between the two reviewers.

Meta-Analysis

The meta-analysis was carried out on the correlation between S-RPE and TD, as well as S-RPE and PL. Funnel plot did not indicate any publication bias (Fig. 3.1, 3.2). Regarding the correlation between S-RPE and TD, a significant positive effect was observed ($k=10$; $r=0.73[0.64-0.82]$; $p<0.001$; $I^2=46\%$). Indicating that greater TD relates to greater S-RPE. Moreover, a strong significant positive effect was observed between S-RPE and PL ($k=9$; $r=0.76[0.68-0.84]$; $p<0.001$; $I^2=38\%$), indicating that greater PL relates to greater S-RPE.

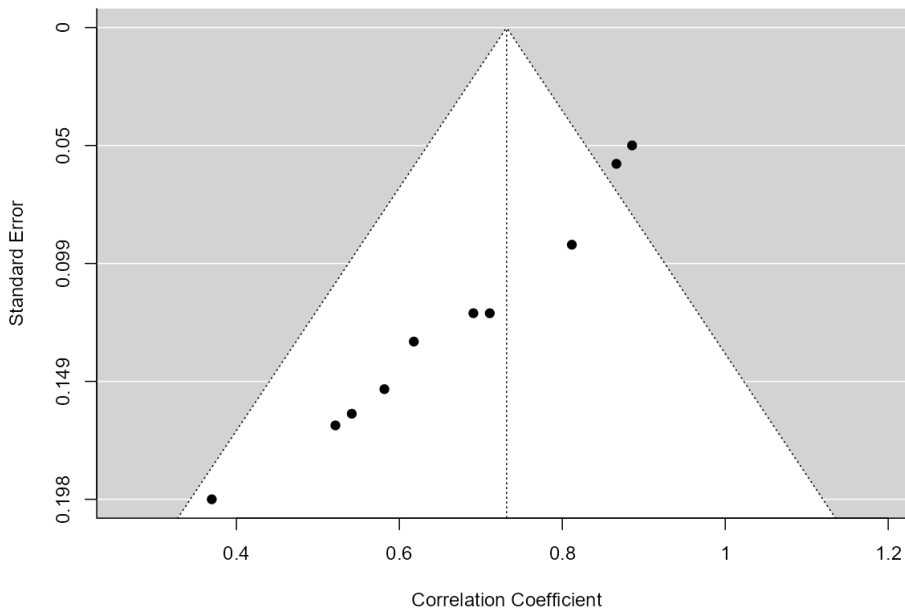


Fig. 3.1 Funnel Plot Total Distance

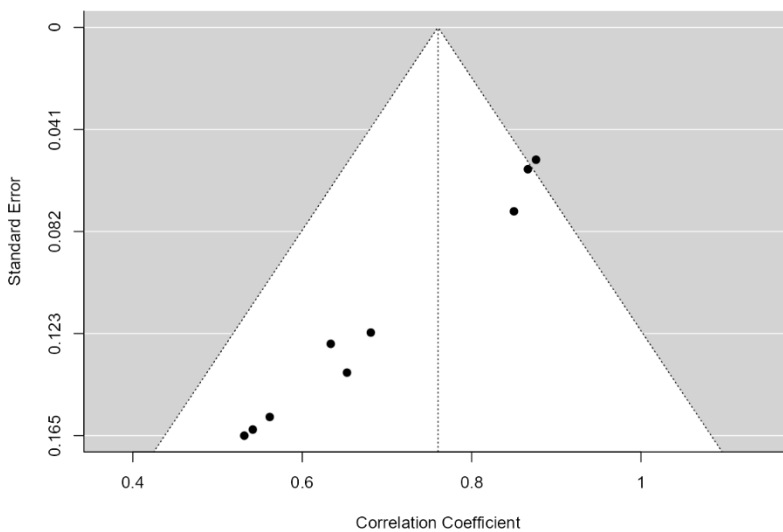


Fig. 3.2 Funnel Plot Player Load

Correlation between External and Internal Loads

The relationship between EL and IL indicators has been examined by eleven studies (85, 175-178, 318, 319, 324-327). A strong correlation between IL and EL was found throughout these studies. In particular, positive correlations between S-RPE and EL variables were highlighted in nine studies (85, 175, 177, 318, 319, 324-327). EL variables should be grouped into three main categories: distance, acceleration/deceleration, and number of impacts, as reported in Table 3.1. It is also

important to underline that the studies showed that S-RPE was more associated with volume indicators (e.g., TD, LRI) than intensity indicators. In particular, the correlation between S-RPE and ELi was lower when high intensity thresholds were considered (HSR and VHSR distance, HIE $>2.5 \text{ m}\cdot\text{s}^{-1}$, and HIE $>3.5 \text{ m}\cdot\text{s}^{-1}$) (85, 175-178, 326). Moreover, to monitor different trainings, a combination of EL indicators is more related to S-RPE when compared to assessing this relationship one parameter per time (85, 324, 325). Thus, some authors combined the variables to create new indexes aiming to better represent TL.

External and Internal Loads integrated approaches: new indexes/ratios

Five studies used different approaches to create a new index or ratio for IL and EL (197, 214, 215, 301, 302). Indices/ratios list is shown in Table 3.1. Grünbichler et al. (2020) created a workload index (Effindex) as the ratio between equivalent distance and TRIMPmod (modified training impulse that describes time spent in certain HR zones multiplied by a weighting factor) (301). This index, analysed during matches, was influenced by sprinting distance, TD, Polar training load (PTL), and training duration (301). Additionally, Suarez-Arrones et al. (2015) and Torreño et al. (2016) used Effindex to quantify the match stimuli dose-response (214, 215). These authors defined Effindex as the ration between mean speed in $\text{m}\cdot\text{min}^{-1}$ divided mean exercise intensity (%HRmax) for every entire first half of the match (214, 215). These authors detected that the higher the overall running performance during the full match was the higher Effindex was (214, 215). Additionally, Derbidge et al. (2020) proposed three different ratios to assess the players' loads: TD/HRe, PL/HRe, and ED/HRe (197). Moreover, Malone et al. (2018) used EL/IL ratios founding that, during trainings, players with a Z-score of -1 reduced both high-speed and maximal running (302).

Predicting Internal Load

Five studies aimed to predict IL using EL indicators (16, 312, 313, 321, 328). Two studies predicted HR with standard statistical analysis (321, 328) and three studies predicted RPE from EL variables using ML (16, 312, 313). The first two studies used GPS indicators for HR and related measures prediction (TRIMP) (321, 328). Lacome et al. (2018) found a large correlation between HR and GPS variables detecting that the greatest predictors were the force load and the mechanical work (321). Moreover, another study showed that total number of accelerations ($>2.5 \text{ m}\cdot\text{s}^{-2}$) and high-intensity repeated efforts are predictor of TRIMP and %tHR80 (328). The remaining three studies applied ML approaches

Association between EL and IL indicators and injuries

Three studies investigated EL and IL associations with non-contact muscular injuries (i.e., acute and overuse) (320, 322, 323). They found that IL and EL indicators were positively related to injuries (320, 322, 323). High Acute Chronic Workload Ratio (ACWR) for S-RPE (320, 322), total high speed running (THSR) distance $>20 \text{ km}\cdot\text{h}^{-1}$ (320), large and rapid weekly changes in HSR and SR distances (323), and higher cumulative HSR and SR workloads (323) were found to be related to an increased IR. Conversely, medium levels of ACWR for acceleration effort (ACCeff, $>1 \text{ m}\cdot\text{s}^{-2}$), DECCeff, S-RPE (320), moderate HSR, and sprint running (SR) distances (323) were found to be related to a decreased IR. Moreover, it was found that high physical fitness levels were related to a lower IR (323). Furthermore, Lu et al. (2017) found that S-RPE was high in all 3 weeks prior the injury week (322). Despite promising results through correlations were presented, a predictive complex model (such as ML) could be a better approach to determine predictions about IR and other training components.

Predicting injuries through EL and IL indicators

Only a study, conducted by Vallance et al. (2020), investigated the use of ML predictive models for IR considering both IL and EL over both 1-week and 1-month period (311). Considering 1-week injury prediction, results as satisfaction, pleasure and RPE were the most relevant for precision (i.e., how many of those injuries predicted really happen) and recall (i.e., of all injury examples, how many of those we correctly predicted) (311). As concern 1-month injury prediction, author detected that current pain was the most relevant variable for IR prediction, while average pain in the last 2-3 weeks was the most accurate (i.e., how many examples we correctly predicted) predictor (311). Also, age, weight, and shape related features were as much relevant for IR accuracy; while worries, fatigue sensations, and EL variables were the most relevant IR precision (311). Summarily, for determining IR factors pre-session questionnaires (to assess sleep quality, fatigue, shape, and mood) and post-session questionnaires (to evaluate satisfaction and pleasure) and RPE were the most suitable indicators to predict IR (311).

DISCUSSION

The first aim of the current systematic review and meta-analysis was to investigate the interaction between internal and external training load indicators, and, consequently, to find the relationship between training load indicators (TLI) (both IL and EL) and injuries in professional soccer players.

In general, studies demonstrated a positive correlation between IL and EL indicators. In detail, RPE, S-RPE, and HR were associated with different EL indicators. New indexes or ratios (integrating EL

and IL) to enhance knowledge regarding TL and fitness status were also implemented. Moreover, a positive relationship between EL and IL indicators and IR was also observed in only three studies (320, 322, 323). Furthermore, efficient prediction of HR (using traditional statistical methods) (321, 328) and RPE/S-RPE (using ML) were found (16, 312, 313). Only one study was found that successfully predicted IR through ML approaches (311). The results showed that ML approaches are poorly used in professional soccer to predict the effect of training (IL responses to a given EL) and IR.

Relationship between External and Internal Load indicators

A general positive correlation between IL and EL indicators were detected in previous studies (300, 329). Casamichana et al. (2013) reported that PL and TD were significantly correlated with HR and derived measures (e.g., EDW TRIMP) in elite soccer players, and with S-RPE in semi-professional soccer players (289). Only one included study found a small positive correlation using total body load (TBL, derived by acceleration zone forces provided in “g” force) and S-RPE (319). This result could be due to TBL, in their computation, does not consider motion mode and influence of specific actions on energy expenditure (319).

Three studies detected a positive correlation between different additional indicators and EL and IL such as the Hooper Index (HI) score (using a scale that includes fatigue, stress, muscle soreness, and quality of sleep) (299, 330) and creatine kinase (CK) levels (298) with new specific S-RPE indexes relative to limbs effort (S-RPE-L) and breathlessness (S-RPE-B) .

The findings of the review showed that S-RPE and HR derived measures were more associated with volume (i.e., TD, LRI) than intensity indicators. In particular, it was found that the correlation is lower between IL and training volume when intensity thresholds increase (175, 177). Moreover, Scott et al. (2013) reported that cardiac response is more associated with distance covered at low speeds compared to high speeds distance (178, 179). This could be due to the role of anaerobic metabolism, mostly involved during short high-intensity activities, which in turn can lead to HR underestimation (178, 179). Similarly, other authors referred to the intermittent nature of soccer to justify the lower association between S-RPE and intensity, whereby it can result in the underestimation of RPE and S-RPE (85, 178). Moreover, despite it is widely used, it has been speculated that RPE could not be specific to assess IL in soccer training tasks. In addition, RPE could be underestimated in specific-ball drills, and it seems to be more related to non-specific metabolic activities in which HR has a linear response (85, 178).

The exclusive use of speed derived indicators to assess intermittent activities should be limited. In fact, only one of the included studies reported that HSR distance, distance per minute, and decelerations distance per minute were significantly associated with RPE (324).

According to our results, PL (derived from accelerations) is largely associated with S-RPE (85, 176, 178, 179, 331-333). As well, Gaudino et al. (2015) reported that metabolic power (derived by speed and accelerations) is more appropriated than only speed to assess performance demands, emphasizing again the role of accelerations (85).

The use of a combination of EL indicators is better related to S-RPE than using only one parameter per time to monitor the different types of training in soccer (85, 324, 325). Nevertheless, integrated approaches considering both EL and IL indicators were used to better assess TL in professional soccer.

External and Internal load new indexes

The results of the current review showed that in professional soccer new indexes or ratios that integrated IL and EL were adopted different times to assess the performance in soccer players. As a matter of fact, one study used ratios between only EL parameters to monitor players' performance (training/match ratio = weekly load/match demands) (304), while other studies integrated both EL and IL indicators (287, 303, 307, 334-338). Although these studies allowed an integrated approach (using both EL and IL), they could not enough to detect the global TL. Indexes only explain the individual internal response to a given EL. Moreover, none of these indices were used to predict IR.

Predicting Internal Load (HR) through External Load

Five of the included studies have investigated the possibility of predicting IL through EL indicators (16, 312, 313, 321, 328). Specifically, the prediction of HR through EL was investigated using traditional statistical analysis to assess players' fitness and readiness (321). HR values are more reliable to monitor continuous running activities (on long distances) than the soccer performance. Indeed, HR slowly adjust to stimuli during repeated short bouts of high-intensity activity (general and sport-specific/with and without ball) causing an inappropriate underestimation (178). Hence, monitoring or predicting HR is not enough to determine players' efforts (i.e., TL). As highlighted in the literature, traditional statistical analysis is less applicable to achieve appropriate prediction. ML approaches are probably more useful, despite they are still infrequently used in professional soccer (16, 311-313).

Association between External and Internal Load and injuries

Our results showed that a relationship between EL and IL with non-contact IR could exist. In fact, the association between IR and TL was largely investigated in soccer (292, 320, 322, 323, 331, 339-352). However, Impellizzeri et al. (2020) reported that the use of TL data in injury prevention is not widely supported by evidence because no author has yet established “the causal link between training/match load and injuries” (353). Authors provided only associations or not externally validated prediction models, hence answers to the “injury problem” are difficult to find considering only the TL measures (or a specific EL or IL variable). Despite these important considerations, the TL could play an important role in the occurrence of injuries because they occur when players are exposed to a specific load (8).

Machine Learning approach for predictions

Only one study, conducted in professional soccer, integrated EL and IL to predict injury (311). While three studies predicted IL considering EL indicators (16, 312, 313). Due to the large and multidimensional dataset nowadays available in sports, ML approaches are suggested for events’ prediction (354). We noted different ML methods used as reported in Tables 3.2 and 3.3. However, the most used method was the Decision Tree classifier (309). Claudino et al. (2019) also reported that the other ML models for IR prediction that frequently used in team sports were artificial neural networks, support vector machine, and Markov process (308).

Machine Learning, Training Load, and RPE/S-RPE prediction

The scientific literature showed that RPE/S-RPE prediction is feasible by assessing EL using different ML approaches (16, 312, 313). Actually, Wiig et al. (2020) stated that EL high-intensity variables have been better used in multiple regression analysis to predict RPE and S-RPE (177). Similarly, two other studies found an accurate prediction ability to assess IL by EL by using ML models (85, 285). Consistently to our results, ML analysis revealed that session distance, HSR, and distance run each minute were the other most predictive variables for RPE prediction (285).

The prediction can be a useful tool to manage players’ training because IL may be affected also by psychological aspects (36, 311, 331, 355). Specifically, we know that RPE is affected by the workload performed in the previous training weeks, while S-RPE reflects the workload of current training sessions (16). Thus, the psychological tensions (e.g., the distance to the official games) could be fundamental aspects affecting both the RPE and S-RPE (16).

Machine Learning, Training Load, and injury prediction

The ability to predict injuries in professional soccer through TL indicators was investigated by few articles (310, 311, 356). Only a study that predicted IR using both EL and IL through ML (311) has been detected. Authors found that for 1-week injury prediction, IL features were more accurate, while for 1-month IR prediction, the best performance was reached combining IL and EL (311). Another study found that, using linear regression, the distance covered in training and matches can impact on the incidence of overuse injury (356). Similarly, Venturelli et al. (2011), using Cox regression, showed that previous injuries, ΔJH (jump index), and height were negatively correlated to thigh-strain occurrence (357). Other studies investigated IR prediction using ML. In this vein, Rossi et al. (2018) predicted injuries in soccer players via a multi-dimensional analysis in which only GPS measurements were applied (310). Promising results were also found in elite youth football players, applying anthropometric, motor coordination, and physical performance measures in ML analysis (358). Moreover, another study conducted in elite soccer players examined whether the use of ML can improve the capability of different neuromuscular tests to identify IR (354). The ML model was very sensitive to asymmetry, knee valgus angle, and body size in youth football players (354). Therefore, it was suggested by those studies that implement ML for injury prevention in sports should be developed with a high methodological quality (309) (348).

CONCLUSION

Our systematic review showed that EL and IL are widely employed in TL monitoring for professional soccer players. We observed that associations between IL and EL and their relationship with injuries could exist.

Comparing statistical analysis approaches, ML seems to be the most suitable for IR prediction. However, determining the cause-effect mechanism of multifactorial phenomena seems not feasible. Important aspects are missing, including the cognitive and emotional load, load due to the use of the ball, and all neuroendocrine factors. Moreover, although the RPE is widely used in both scientific and practice field to monitor the IL, we think that is not sufficient for soccer.

Further studies using ML are recommended to better understand the intuitive, but not clearly established, relationship between loads and injuries in professional soccer also by developing a formula that included both IL and EL, to predict injuries with ML.

3.2 Association between match-related physical activity profiles and playing positions in different tasks: a data driven approach

Pillitteri G, Rossi A, Cintia P, Trecroci A, Petrucci M, Battaglia G. (2024). Association between match-related physical activity profiles and playing positions in different tasks: A data driven approach. *J Sports Sci.* 2024 Mar;42(5):465-474.

Introduction

During a soccer match, players are required to address different both technical activities such as shot, passing, header, tackles and running at different speed intensity in the form of high-speed running, accelerations, and decelerations tasks (8, 359) eliciting both metabolic and neuromuscular demands. In soccer, physical performance refers to intermittent cyclic and acyclic activities characterized by aerobic and anaerobic demands (360). As a matter of fact, 150–250 different actions and 1100 changes of direction were performed by players during a match (361). Professional players cover a total distance of between 10 and 13 km during a match (362) including low intensities, while 22–24% is spent at intensities above 15 km/h, 8–9% above 20 km/h, and 2–3% above 25 km/h. Moreover, players can perform between 600 and 650 accelerations during a match highlighting their relevant contribution on physical demand. These demands were found to be related to playing positions (145, 256, 363). As a matter of fact, previous studies have shown differences in external load (EL, i.e., distance, speed and accelerations) (364) and internal load (IL, i.e., through physiological factors assessment including heart rate and derived indices and/or rate of perceived effort scale) (365) by playing position during both training and matches (366, 367). In particular, a previous study has shown that both central and wide midfielders spent most of the time in moderate- and high- intensity activities, also covering more total distance than other roles during a game. Moreover, they spent less time in low intensity showing shorter recovery bouts compared with other playing positions (148, 366, 367). Differently, defenders spent significantly less time sprinting and running compared with other roles (201). Additionally, central backs showed the longest recoveries between consecutive high-intensity efforts (368) and the shortest time in low intensity activities (366). It is worth noting that players in wide positions (i.e., wide defender and wide attacker) accelerated significantly more than central ones (364). Notably, each position requires specific physical performance that could change in accordance with the tactics imposed by the coach along with other contextual factors such as match scoring and difficulty, i.e., level of opponents (369).

In order to reflect the physical, technical, tactical, and cognitive demands of a match, Small-Sided Games (SSG) and Match-Based Exercises (MBE) may represent valid soccer-specific training solutions. If opportunely employed by practitioners, these particular drills are capable of driving both metabolic and neuromuscular physical demands differently (370). SSGs are among the most common

drills, they are performed in a small area of the pitch with a reduced number of players and specific rules that allow modulating the training intensity (371). MBE reflects soccer tasks carried out in larger pitches, with a greater number of players compared to SSG and games rules defined in accordance with Official Matches (OM). From a tactical perspective, MBE are more similar to match requests than SSG. It is worth noting that SSG does not completely reproduce the actual game-related physical demands (189). Rather, it can be considered a high-intensity task that stresses the players' neuromuscular components (189).

It is known that both EL and IL can be affected by manipulating game and scoring rules, the number of players per team, and the pitch size (372). Regarding pitch size, $\sim 300 \text{ m}^2$ per player is the average match density experienced by players during regular matches (373), while SSGs have been performed in more dense conditions (e.g., $\sim 100 \text{ m}^2$ or $\sim 200 \text{ m}^2$ per player) (374). It has also been previously reported that, in a smaller pitch (around 100 m^2 , players' performance is characterised by multiple accelerations, decelerations, and changes of direction involving high neuromuscular demands). Differently, in a large field, such as in the Match Based Exercises, players address more high-speed running tasks (373), eliciting more metabolic responses such as metabolic power and derived metabolic measures. This is probably due to the higher speed reached by players in large fields compared to smaller ones observed in Small-Sided Games (370). Hence, increasing the field dimension could be a proxy for increasing also acute physiological demands (i.e., heart rate, blood lactate, and RPE) (375). In this regard, coaches can consider "intense" tasks based on the type of stimulus (i.e., metabolic or neuromuscular) undergone by a player during a specific drill.

Although the literature has reported a lot of information on SSG and MBE, understanding the real impact of these specific drills on soccer performance could be a challenge for practitioners to schedule training weeks. Defining the intensity of specific soccer drills could help practitioners planning training sessions by providing the optimal stimulus for the players. The framework we propose in this study would aim to make it possible. In particular, it can assess the physical impact of different drills (matches, SSGs, and MBEs) for different players' playing positions. Specifically, through this approach it will be possible to define the intensity of a soccer exercise by indicating whether a stimulus is predominantly neuromuscular or metabolic also by playing position. Therefore, the first aim of this study is to discriminate roles in soccer through EL profiles considering different types of soccer drills using a supervised Machine Learning approach. Additionally, the second aim is to create physical activity profiles based on EL through a data driven approach: official matches' data become a comparison key to evaluate the intensity of physical tasks executed during a training session. Given the amount and the complexity of the available data, the use of Machine Learning

(ML) (376) approaches could help to outline the impact of these exercises on soccer's performance based on EL and tasks' density data (m^2 per player).

Methods

Subjects

Twenty-eight semi-professional soccer players (age: 25.21 ± 6.18 years, height: 183.42 ± 6.41 cm, weight: 75.24 ± 7.02 kg) competing at the fourth Italian division (Serie D) were recruited for this study during the 2019-2020 season. Due to the different physical demands, the goalkeeper was excluded from this study (377, 378). In this paper, players were separated into six playing positions ($n = 7$ central back, $n = 7$ external strikers, $n = 2$ fullback, $n = 5$ midfielder, $n = 4$ striker, and $n = 3$ wide midfielder) in accordance with the zone of the pitch they used to play. A total of 996 training sessions (35.57 ± 21.79 per player) were recorded throughout the soccer season. To reduce inter-training variability between weeks induced by short microcycle, data from regular in-season training weeks (i.e., 6 days between matches) were used. A total of 33 weeks composed of 5 training days and 1 day off were used in this study. All the participants signed an informed consent before taking part in the experiment. The study, which complies with the principles of the Declaration of Helsinki, was approved by the Bioethics Committee of the University of Palermo (n. 68/2021).

Soccer-specific drills

Three different drills were evaluated in this study:

- Matches (official and friendly matches; $n = 384$): we considered a match density of about 300 m^2 .
- Small-Side Game (SSG; $n = 296$): SSGs were performed in a small area of the pitch with a reduced number of players compared to regular matches and carried out with specific rules (e.g., number of touches of the ball, goal crossing the goal line, the use of three soccer goals). In this study, we included different types of SSG based on m^2/player (around $100 \text{ m}^2/\text{player}$), as shown in Table S3. SSGs were grouped by a data driven approach (supplementary material S1) as follows: Small Density with High Neuromuscular and Low Metabolic indicators (SD-HN-LM-ssg); Medium Density with Low Neuromuscular and Metabolic indicators (MD-LN-LM-ssg); Large Density, High Neuromuscular and High Metabolic indicators (LD-HN-HM-ssg); Very Large Density with Medium Neuromuscular and Metabolic indicators (VLD-MN-MM-ssg).

- Match-based exercises (MBE; n = 316): MBEs represent soccer specific tasks carried out in a larger area of the pitch and a relatively larger number of players compared to SSGs. Specific rules related to technical-tactical behaviours (similarly to matches' demands) characterise these tasks. The presence of both goalkeepers and the directionality of the game (i.e., the team in possession must score a goal in the opposing team's goal) makes these drills similar to friendly matches with the difference that they are played in smaller spaces and there are rules specific tactics compliant with the tactical needs of the coach. Moreover, the playing positions are defined for each player.
- In this study, we included different types of MBE based on m²/player (around 200 m²/player) as shown in Table S4. MBEs were grouped by a data driven approach (supplementary material S1) as follows: Medium Density with Low Neuromuscular and Metabolic indicators (MD-LN-LI-mbe); Large Density with Medium Neuromuscular and Metabolic indicators (LD-MN-MI-mbe); Small Density with High Neuromuscular and Metabolic indicators (SD-HN-HI-mbe).

Data recording

Both matches and soccer-specific drills were played on a third-generation artificial pitch or natural grass. All players performed a 15-minute warm-up before performing MBE and SSG and a typical 25-minute pre-match warm-up before matches.

Data was collected through a Global Position System (379) (GPS unit, Qstarz BT-Q1000EX, 10 Hz) (380) positioned on the upper back inserted in a special vest. The GPS device was started 15 minutes prior to the assessment to make available the acquisition of satellite signals. The average number of satellites in view was 12, the average horizontal dilution of precision (HDOP) was 0.8 (381). All data was acquired through a dedicated software (LaGalaColli V: 8.6.4.3) during the entire 2019-2020 soccer season. EL indicators (normalized per minute) and recorded as global time (considering when the ball is both in and out of play and excluding recovery between set), obtained from GPS devices and considered in this study were both metabolic and neuromuscular, and they are detailed in Table 3.4.

Table 3.4 EL indicators descriptions

Feature	Description

Watt	Metabolic Power ($W \cdot kg^{-1}$) was calculated by multiplying EC (in $J \cdot kg^{-1} \cdot m^{-1}$) by running speed (v ; in $m \cdot s^{-1}$) at any given moment (i.e., every 0.2 s): $P_{met} = EC \cdot v$. In order to assess metabolic power, considering the energy expenditure and derives, the equation developed by di Prampero et al. (382) established on previous studies by Minetti et al. (383) and Osgnach et al. (70) was adopted.
%W>35W	Percentage of metabolic power with intensity > 35 W.
n° actions int/min	Number of intense actions per minute. The threshold considered to establish the intense actions was $20 W \cdot kg^{-1}$ which represents the metabolic power when running at a constant speed of approximately $14.4 km \cdot h^{-1}$ (high speed) on grass (70).
dist/min	Metres covered in a minute.
PrT/min	Passive Recovery time per minute represents the sum of the seconds in a minute (for each minute) in which the player moves at a metabolic power between 0 and 5 W (i.e., 0-8 Km/h).
%int acc	This indicator represents the percentage of the number of accelerations $>2 m/s^2$ out of the total number of accelerations.
%int dec	In an opposite way to the previous one, this parameter indicates the percentage of the number of decelerations $<-2 m/s^2$ out of the total number of decelerations.
CdD/min >30	The number of changes of directions higher than 30° per minute.

Playing position prediction

Four machine-learning classifiers were trained to predict the players' playing positions based on EL parameters respectively in all the soccer-specific drills. The algorithms tested in this paper are Decision Tree Classifier (DTC), Random Forest Classifier (RFC), Extreme Gradient Boost Classifier (XGB), and Multinomial Logistic Regression (MLR). Moreover, a baseline classifier (Dummy) based on stratified approach (distribution of playing positions) was assessed in order to validate the prediction ability of the machine learning models. The models were trained in the 70% of the dataset, while the remaining 30% of the dataset was used as a test set. The metrics used to evaluate the model's goodness are described in Supplementary material S2.

Match' intensity profiles

A data driven approach was used to profile players in accordance with intensity demands during Matches. In particular, the data was initially normalized between 0 and 1, and then a feature dimension reduction was performed by using Principal Component Analysis (PCA). The elbow approach based on the explained variance was used to detect the best number of components for PCA.

A non-supervised machine learning model (k-means) based on the components derived from PCA analysis was fitted to partition n observations into k clusters in which each observation belongs to the cluster with the nearest cluster centroid. A silhouette analysis based on the k-means model was conducted to detect the best number of clusters into each drill. Finally, we assessed how the physical activity profiles detected in matches were distributed in SSGs and MBEs.

Results

Playing positions prediction

Table 3.5 shows the predictive performance in each drill. The players' positions in OM are more accurately discriminated by RFC (57%) compared with the other models. The very low accuracy of the baseline model (16%) indicates that RFC is a valid model able to distinguish between players' position in matches by assessing intensity parameters. In particular, %W>35W, n° actions int/min, and metabolic power (Watt) are the three most important features used by RFC in the decision-making process showing an importance of 21.62%, 13.24%, and 13.08%, respectively.

In SSG, the playing positions of players are difficult to detect (RFC accuracy = 36%). The low ability to discriminate between players' playing positions during SSG and the low increment in predictive ability of RFC compared to baseline model (~12%) indicate that this kind of drill could not accurately represent the performance model of each role in the matches.

During MBE, RFC is able to predict 40% of the total players' playing positions. It is a valid model to discriminate the roles of the players due to the higher accuracy compared with baseline (17%). Similar to the results obtained in Matches, the three most important features used by RFC to predict the players' playing positions are %W>35W (21.30%), n° actions int/min (12.90%), and metabolic power (11.67%).

For more details about the prediction goodness of the models, see Figure S3.

Table 3.5. Predictive performance (weighted average of all the classes) of the machine learning algorithms and the baseline. The best model for each task was highlighted in green, while baseline (dummy) predictive performance was highlighted in grey.

Task	Model	Precision	Recall	F1-score	Accuracy
Matches	DTC	0.45	0.47	0.45	0.47
	RFC	0.56	0.57	0.56	0.57
	XGB	0.57	0.56	0.55	0.56

	MLR	0.47	0.51	0.47	0.51
	Dummy	0.16	0.16	0.16	0.16
SSG	DTC	0.29	0.29	0.29	0.29
	RFC	0.35	0.36	0.34	0.36
	XGB	0.32	0.35	0.33	0.35
	MLR	0.29	0.34	0.30	0.34
	Dummy	0.22	0.24	0.23	0.24
MBE	DTC	0.29	0.27	0.28	0.27
	RFC	0.35	0.36	0.35	0.36
	XGB	0.28	0.26	0.27	0.26
	MLR	0.38	0.40	0.38	0.40
	Dummy	0.17	0.17	0.17	0.17

Matches' intensity profiles

PCA analysis indicates that 3 components explain 97.63% of the data variance during Matches. By using these 3 components, it is possible to distinguish among 5 players' profiles (silhouette score = 0.34). We label them as very low intensity (VLI), low intensity (LI), moderate intensity (MI), high intensity (HI), and very high intensity (VHI).

Table 3.6 shows the centroids of the 5 profiles detected by the k-means analysis. Figure 3.3 reports the distribution of playing positions in each matches' intensity profile. During 62% and 50% of the time, full backs and central backs performed matches in VLI and LI profiles, respectively. Differently, external strikers usually show HI profiles (43%), while strikers execute different performances in each match showing 36%, 24%, and 29% of the time LI, MI, and HI profiles. Additionally, midfielders played with MI and VHI physical activity profiles for 50% and 37% of the time, respectively. Finally, 24%, 26% and 38% of the time, wide midfielders played with LI, MI, and VHI profiles, respectively.

Table 3.6 Matches' intensity profiles obtained by a data driven approach. The data were reported as mean (Standard deviation). VLI, LI, MI, HI, and VHI correspond to very low intensity, low intensity, moderate intensity, high intensity, and very high intensity, respectively.

	VLI	LI	MI	HI	VHI
Watt	8.79 (0.49)	9.97 (0.40)	10.92 (0.35)	11.05 (0.37)	12.03 (0.44)
dist/min	92.64 (4.70)	104.31 (4.11)	114.88 (3.01)	114.86 (3.40)	126.07 (3.50)
%int acc	7.60 (1.30)	8.85 (1.32)	9.24 (1.28)	10.22 (1.22)	10.27 (1.61)
%int dec	8.27 (1.29)	9.52 (1.31)	10.16 (1.26)	10.02 (1.36)	10.63 (1.38)
CdD/min >30	14.39 (1.13)	15.04 (1.38)	15.58 (1.44)	14.91 (1.31)	15.26 (1.34)
%W>35W	21.51 (4.14)	21.94 (5.72)	17.58 (3.75)	27.31 (2.82)	19.35 (2.95)
n° actions int/min	2.48 (0.45)	2.99 (0.29)	3.57 (0.35)	3.18 (0.39)	3.94 (0.30)
PrT/min	22.21 (1.91)	18.44 (2.73)	15.00 (2.41)	14.00 (2.12)	11.12 (2.19)

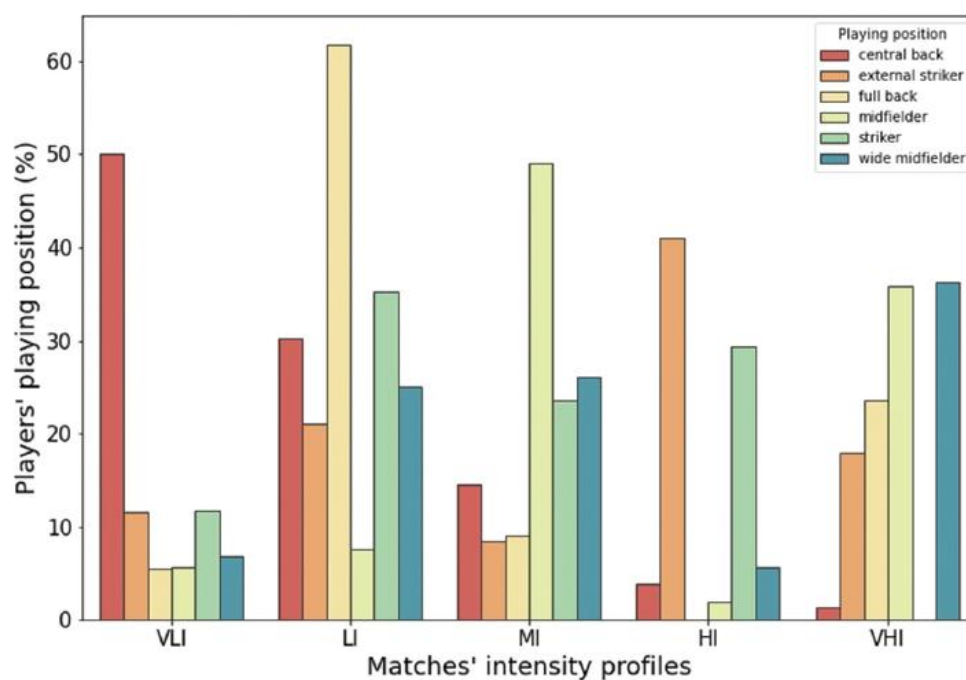


Figure 3.3 Percentage of playing position in each players' matches' intensity profiles. VLI, LI, MI, HI, and VHI refer to very low intensity, low intensity, moderate intensity, high intensity, and very high intensity, respectively.

Figure 3.4 and 3.5 shows the difference in occurrence distribution of matches' intensity profiles detected in OM for SSG and MBE in each player's playing position, respectively. In accordance with the different typologies of SSGs and MBEs and with the players' playing positions, the distribution of matches' intensity profiles changes. Moreover, different patterns of intensity profiles were detected between sport specific drills (i.e., SSG and MBE) and OM. Considering SSG exercises (Figure 3.4), central backs performed most of the matches at moderate-low intensity reflecting a similar trend in all the SSG typologies. LD-HN-HM-ssg induces the highest intensity in the players competing in this playing position. Moreover, external strikers often performed high intensity matches (HI and VHI) that could be simulated only by SD-HN-LM-ssg and LD-HN-HM-ssg. Additionally, full backs resulted in LI, but in all SSG types performed more MI. 43% and 38% of times midfielders performed matches in MI and VHI profiles. SD-HN-LM-ssg and VLD-MN-MM-ssg show a similar MI pattern, while LD-HN-HM-ssg produce more intense activities. Strikers and midfielders performed all the physical activity profiles in similar percentages, but SSG typologies show specific patterns that do not reflect the OM ones.

Figure 3.5 reports the difference in occurrence distribution of matches' intensity profiles detected in OM for MBE in each player's playing position. During SD-HN-HM-mbe the players performed the highest percentage of VHI compared to other MBE types and OM. Differently, MD-LN-LM-mbe results in higher percentage of VLI and LI activities and lower HI and VHI ones compared to other MBE types and OM in external strikers. Similar to MD-LN-LM-mbe, full backs presented the highest percentage of LI in OM, while others MBE types showed highest intensity. Similar patterns were detected between OM and MBE types in strikers and wide midfielders.

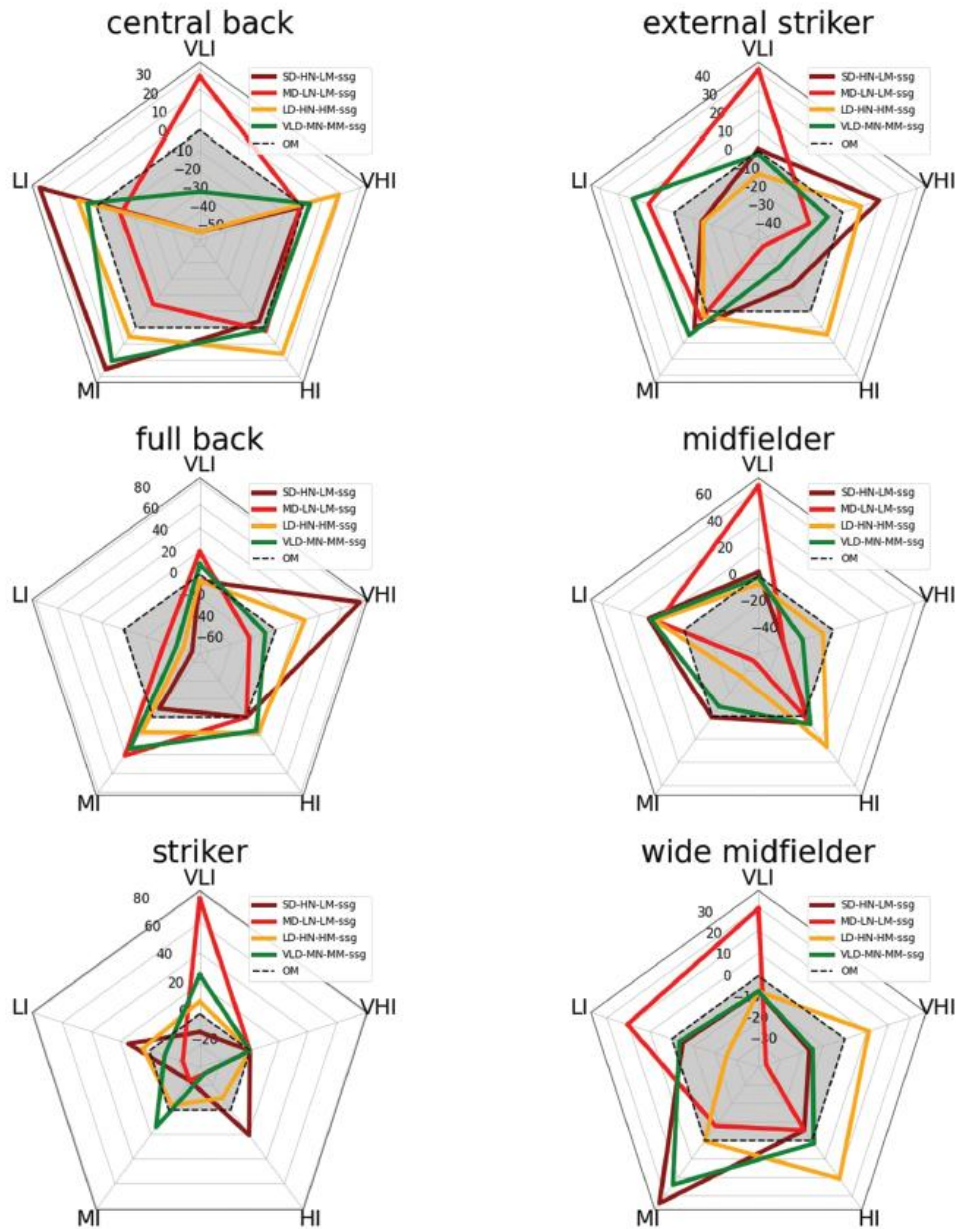


Figure 3.4 Percentage difference of matches' intensity profiles occurrence between each SSG group and OM for each playing position.

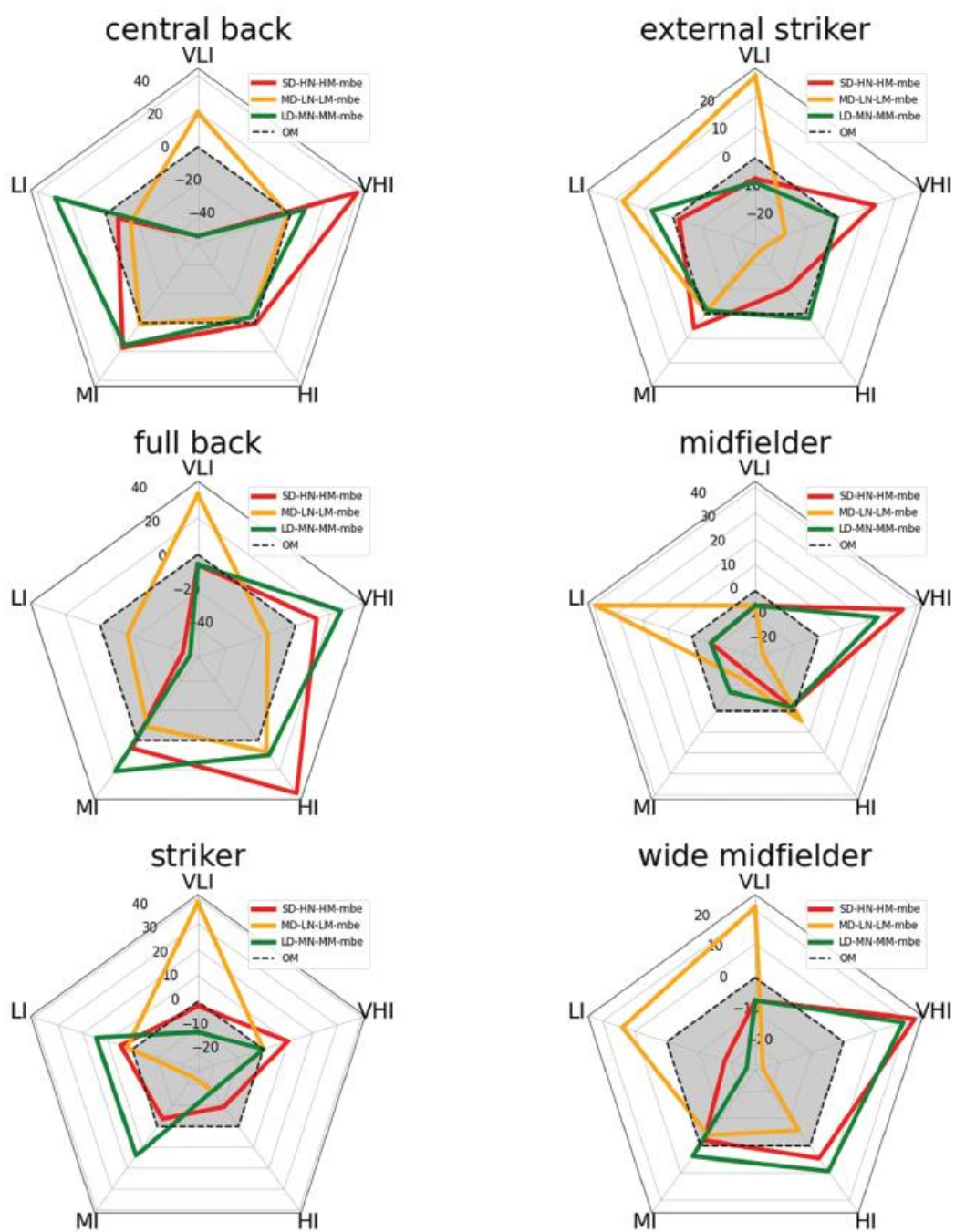


Figure 3.5 Percentage difference of matches' intensity profiles occurrence between each MBE group and OM for each playing position.

Discussion

The first main result of this work is that the players' playing positions during matches and MBE are characterised by specific metabolic and neuromuscular stimuli, while during SSG players show similar physical stimuli even if they play in different playing positions (Table 3.5). Moreover, the framework of data analytics provided in this paper permits to profile the players' metabolic and neuromuscular performance during matches with the aim of understanding if the physical demands of a player requested during matches are reflected in the training drills.

In accordance with matches' tactical demands, the usual playing position of a player could vary during a match or between matches and consequently the role-related physical demands (75, 145) change. Hence, for these reasons, the model can moderately discriminate the players' roles in all the matches and MBE examples. As a matter of fact, during matches and MBE, the wide midfielders were often confused with external strikers probably because of similar tactical demands among these two roles. Moreover, as full backs and wide midfielders played in an external pitch position with similar tactical and physical demands, our model showed some prediction errors related to these specific player's playing positions. Finally, midfielders are almost always exchanged with wide midfielders. These results indicate that different physical demands are required by specific roles in Matches and MBE. Differently, the performance model for each role in SSG seems completely different compared to OM. The reason why the players' playing positions are not distinguishable during SSG is that the maintenance of a specific role in these kinds of exercises is not mainly required, despite being rarely assigned, but practitioners used these drills to induce technical and physical stimuli. Worth noting, during the training microcycle prescription process, different types of tasks across the training week are required to elicit the targeted physical stimuli. For example, during the MD-4 the use of SSG expose the players to "special" strength such as acceleration and deceleration, while the players' metabolic response could be limited. Conversely, during the MD-3 players are often exposed larger playing spaces (e.g., MBE) to reach high-speed running distance, sprinting, peak speed, and higher metabolic power (i.e., higher intensity and metabolic stimuli).

This finding corroborates the results of a previous paper in which Riboli et al (252) found that training tasks with goalkeepers better simulated the match intensity. This is because the use of the goalkeepers gives a direction to the game, resulting in a tactical strategy involvement compared to other drills. Moreover, SSG without goalkeepers usually shows higher intensity compared to goalkeeper-based tasks (252). Additionally, based on the low predictive performance of RFC detected in this study, we could speculate that the metabolic and neuromuscular performances are poorly related to playing positions in SSG. The pitch size, the players' density on the field and the exercise

rules induces different metabolic and neuromuscular responses in both SSG and MBE drills. Indeed, some authors reported that specific strength components (accelerations, decelerations, and changes of direction) are emphasised in small spaces, while high-speed running and metabolic stimuli are greater in larger pitch sizes (373, 375, 384). As a matter of fact, Gaudino et al reported an increase in acceleration/deceleration requirements and total number of changes in velocity when the number of players and pitch dimensions decreased in SSG (370).

Profiling players' performance in accordance with the match's metabolic and neuromuscular characteristics would allow coaching staff to fast and easily assess the stimuli sustained by players. Evaluating the match physical performance could be useful to schedule the training program during the weekly microcycle evaluating if the training target and intensity were reached for each player's roles. As shown in Figure 3.3, each player's playing position results in a prevalence of specific matches' intensity characteristics showing that the players' roles are characterised by a specific prestantive model. However, based on match characteristics, players could show a different matches' intensity profile compared to the common one detected for their specific playing position. For example, full backs usually show a prevalence of the LI profile (62% of the time), but 24% of the time they perform in the VHI profile. It is probably due to the different intensity and defensive demands of the match.

Thanks to match profiling, it is possible to assess whether the model detected during a match in a specific player or playing position is mirrored during training drills such as SSG and MBE. Moreover, to train specific metabolic and neuromuscular characteristics, it might be possible for practitioners to assess the type of workload sustained by a player in a specific playing position during such drills. Hence, the choice of a specific SSG and MBE could be made in accordance with the training purpose and intensity (253). As showed in Figures 3 and 4, similar distribution of physical profiles was detected in MBEs compared with OM, while SSGs showed a different distribution. The reason why the players' playing positions show different physical profiles distribution during SSGs compared to the matches one, while similar one during MBEs is related to the different nature of the two tasks. As a matter of fact, MBEs are match oriented due to the fact that it is characterised by similar players' playing positions and rules, while SSGs are more focused on free play without fixing specific roles but with specific rules not often match-related (252, 256).

The study's primary limitation lies in its applicability solely to the specific soccer team under analysis. Variations in player characteristics, team playing styles, and training regimens necessitate a tailored adaptation of our framework for each team. However, this limitation also underscores the advantage of our work's personalized nature. Indeed, our paper introduces an innovative method for

evaluating players' physical performance during both matches and training sessions, eschewing the provision of generalized insights into role behaviors. Thus, the principal strength of our approach lies in its utilization of machine learning, which facilitates the detection of multidimensional patterns within extensive datasets, enabling the assessment of training objectives and intensity characteristics.

Practical Applications

The analysis conducted in this study provides a deeper understanding regarding the roles-specific model. As a matter of fact, to describe the players' performance during matches and comparing it with training exercises in different playing positions, specific matches players' profiles could be obtained from their EL data. The framework used in this work allows practitioners to better recognize the workloads performed by players during training tasks. In detail, this approach permits to detect relevant information from training exercises regarding both target task (i.e., neuromuscular or metabolic) and the task intensity based on EL indicators, the players' density on the pitch, and the type of tasks. Therefore, it is possible to understand if a specific task could be more intense compared to official matches, considering each player's playing position.

In detail, as showed in Figure 3.6, each cluster provide valuable information on the kind of stimuli elicited (i.e., metabolic or neuromuscular) and the physical intensity for each playing position. As regards SSG, clustered as SD-HN-LM showed the smallest density and consequently eliciting high neuromuscular, low metabolic stimuli and good intensity. Cluster MD-LN-LM presented medium density but the lowest intensity as shown for both neuromuscular and metabolic indicators. While cluster VLD-MN-MM revealed the highest density and medium intensity. The highest intensity was found in Cluster LD-HN-HM. Concerning MBEs clusters, MD-LN-LM showed medium density and lowest intensity (due to the highest Tr pass /min) considering all indicators except for %W>35w that presented the highest value. Cluster LD-MN-MM presented the highest density and medium-high metabolic and neuromuscular indicators, while Cluster SD-HI-HN showed the smallest density, highest intensity considering all indicators except %W>35w.

As regards the difference between playing position, Table3.7 shows an overview about the drills clustered (i.e., SSG and MBE) providing the physical intensity (low, medium, high and very high) for each role based on the type of drills selected.

In this way, practitioners could select with more appropriateness the type of task during the scheduling microcycle process based on the suggestions provided by the proposed machine learning model.

Table 3.7 Overview of the difference in physical intensity between playing positions based on the different drills clustered (SSG and MBE). SSG: (SD-HN-LM) – (MD-LN-LM) – (LD-HN-HM) – (VLD-MN-MM); MBE: (SD-HM-HN) – (MD-LN-LM) – (LD-MN-MM). Moreover, VLI, LI, MI, HI and VHI refer to Very-Low-Intensity, Low-Intensity, Medium-Intensity, High-Intensity and Very-High-Intensity, respectively.

PLAYING POSITION	DRILLS TIPOLOGY						
	SSG				MBE		
	SD-HN-LM	MD-LN-LM	LD-HN-HM	VLD-MN-MM	SD-HN-HM	MD-LN-LM	LD-MN-MM
CB	LI	VLI	HI/VHI	MI	VHI	VLI	LI
ES	VHI	VLI	HI	LI	VHI	LI/VLI	LI
FB	VHI	MI	VHI	MI	HI	VLI	MI/VHI
MD	LI	VLI	HI	LI	VHI	LI/VLI	VHI
S	HI	VLI	VLI	VLI	VHI	VLI	LI/MI
WM	MI	LI/VLI	HI/VHI	MI	HI/VHI	LI/VLI	HI/VHI

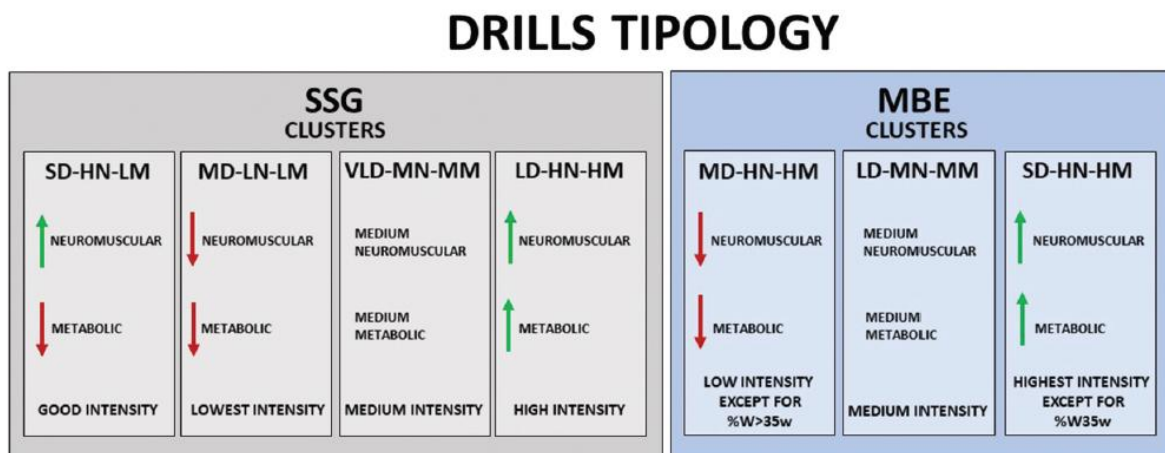


Figure 3.6. Drills cluster framework based on the ML analysis.

Conclusion

Playing position shows specific intensity profiles based on training task targets and on both neuromuscular and metabolic components during both training drills and matches. The framework of data analytics based on the machine learning approach proposed in this paper permits the evaluation of the intensity of soccer tasks to easily and quickly evaluate the physical performance of a player. In this way, practitioners could evaluate the type of stimulus performed by a player in a specific training drill to assess if they reflect the matches characteristics of their specific playing position. Moreover,

practitioners could use this approach to schedule the training program in order to maximise the training effect while reducing the risk of injury by monitoring both intensity and the neuromuscular and metabolic components of each training task.

3.3 Elite Soccer Players' Weekly Workload Assessment Through a New Training Load and Performance Score

Pillitteri G, Rossi A, Bongiovanni T, Puleo G, Petrucci M, Iaia FM, Sarmento H, Clemente FM, Battaglia G. (2024). Elite Soccer Players' Weekly Workload Assessment Through a New Training Load and Performance Score. *Res Q Exerc Sport*. 2024 Dec;95(4):993-1001.

1. INTRODUCTION

Physical training, when is appropriately delivered in accordance with the training goal, induces psychophysiological responses that leads soccer players to reach specific adaptations. In order to elicit a desired athlete's training response, practitioners are used to monitor acute and chronic training effect. Actually, a conceptual framework carried out by Jeffries et al., (17) have reported several training effect categories such as performance, physiological, subjective and other (cognitive, biomechanical, etc.) measures highlighting the lack of a gold standard which include the surrogate (proxy) measures that reflect the training effect construct. The identification of the measurable components and their role within the training process is a paramount on- field practice (i.e., training monitoring) that allows practitioners to adjust and adapt the training periodization program. Noteworthy, training monitoring is crucial to identifying an athlete's adaptation to a training stimuli, as well as minimizing the risk of non-functional overreaching (385, 386).

The training load (TL) in the context of athletic training has been described as “the input variable that is manipulated to elicit the desired training response (387)”. Actually, monitoring of TL in soccer involves multiple measures derived from both external (i.e., the physical activities performed by players derived from training plan) and internal loads (i.e., the actual athlete's psychophysiological response that initiates to cope with the requirements elicited by the external load) (387). Actually, several indicators have been used to monitoring soccer players considering both physiological (e.g.,

heart rate, maximal oxygen consumption and lactate blood concentration (259, 388) and match-demand-related components. Nowadays, these information are derived from Electronic Performance and Tracking Systems (EPTS) (160) devices such as Global Positioning System (GPS) (389, 390) and inertial measurement unit (IMU) (391). Noteworthy, in order to better understand the TL to which soccer players are subjected an integrative approach that consider both external and internal load is guaranteed by conceptual frameworks (387). Indeed, each TL indicators provides only a partial component of soccer TL (392).

Given a lack of gold standard to assess TL and considering the multifactorial nature of physical soccer performance, practitioners should consider several indicators to holistic overview of training effect (392). Actually, it is a tough challenge for the practitioners the management of a big amount of data and the appropriate interpretation of all the variables provided by the EPTS devices (393). Hence, may be useful and necessary the identification and selection of the key performance indicators (394) through specific statistical methods to reduce the dimensionality of datasets (107, 393-395) with the aim of synthesize the soccer physical performance in order to reduce possible communication problems within staff team (221).

Some previous studies have proposed new indexes and ratio that permits to understand the relationship between external and internal load indicators (86, 396) and evaluate the players' injury risk. Actually, as suggested by Impellizzeri et al., TL framework (387), the uncoupling between internal and external load may be used to identify how an athlete is coping with their training program. Moreover, when players perform the same external load (e.g., total distance) with a lower internal load (e.g., average HR), would be assumed to reflect increased fitness level. On the other hand, an increase in internal response when the same amount of external load is performed may be attributed to a fatigued condition or a loss in fitness level. For example, the efficient index (Effindex) given by the ratio between mean speed in $\text{m}\cdot\text{min}^{-1}$ (i.e., external load) divided mean exercise intensity (%HRmax) (i.e., internal load) has been implemented to quantify the match stimuli dose-response (i.e., a physiological response for a given external activity performed) (209, 215). Other studies have investigated the relationship between TL and injuries by using the ratio between acute and chronic workload (ACWR) (397) suggesting the protective benefits of high chronic loads and physical strength against injury by highlighting to avoiding sudden spikes in acute TL (398).

To the best of our knowledge, a global training/match load score has never been implemented considering both external and internal load. Although studies have used external/internal load ratio to identify fitness-fatigue conditions, machine learning methods have not been considered for this

purpose. Therefore, the aims of this studies were to: 1) obtain the key external load indicators in professional U19 soccer through principal component analysis (PCA) starting from several data provided by ISD; 2) calculate both a total training/match load score and an athlete's physical performance score considering both external and internal load indicators; 3) analyse the training microcycle (distance between two official matches [MD system]) through the scores calculated from the external and internal load indicators also considering the differences between playing positions.

2. METHODS

2.1. Experimental Approach to the Problem

In this cross-sectional study, the internal and external training workloads of twenty-four-professional Italian young (U19) soccer players were monitored by using the rating of perceived exertion (CR-10 RPE scale) and a wearable inertial sensor, respectively, during the competitive season from August to February (2022-2023). Soccer players were categorized into six groups according to their role as follows: central back (CB), external strikers (ES), fullback (FB), midfielder (MD), wide midfielder (WM) and Strikers (S).

2.2. Subjects

Twenty-four-professional soccer players (age: $18,7 \pm 0,5$ years, height: 177 ± 6 cm, weight: $67,5 \pm 7,7$ Kg) competing in the U19 Italian Championship were analysed. In detail, 1,280 observations, ($53,3 \pm 28,9$ for each player) (109 training session and 12 Official Matches) have been assessed monitoring both external and internal load. Participants' playing positions were the following: Central Back (CB; $n = 6$), Full Back (FB; $n = 2$), Central Midfielder (MD; $n = 2$), Wide Midfielder (WM; $n = 6$), External Sticker (ES; $n = 5$), and Central Sticker (S; $n = 3$).

The following inclusion criteria were considered: 1) professional male soccer players; 2) no injury in the previous six months. Based on the exclusion criteria, only the goalkeepers were not eligible for the study. The total duration of the training sessions (number of training observation = 1,280) was 97 ± 20 min and mainly included technical-tactical team tasks along with some general physical exercise without ball (e.g., high intensity interval training, HIIT). Strength and conditioning exercises were performed twice a week (i.e., one session in the gym and one session on the pitch). Moreover,

the game duration was 83 ± 16 min (number of matches observation = 118). In total, 12 matches and 118 trainings ($1,124 \pm 113$ minutes per week) were analysed in this study. All participants signed an informed consent before taking part in the data collection. The Bioethics Committee of the University of Palermo (n. 68/2021) approved the study, which complies with the principles of the Declaration of Helsinki.

2.3. Procedures

Participants were monitored during training and official matches performed on a third-generation artificial pitch or natural grass during the 2022-2023 season. All players performed a typical 25-minute pre-match warm-up before OM and 30' before training (15' specific activation in the gym and 15' on field warm-up). Internal Load data was collected through RPE scale. TL for each participant was calculated according to the session-RPE method of Foster et al. (2001) 30 min after each session. The duration (minutes) and each RPE training session were recorded for players using smartphone applications (i.e., WhatsApp through a broadcast list). TL from each session for each player was calculated from the product of the session duration and the player's RPE (Foster et al., 2001). The training session duration included warm up, cool down and rest between tasks.

External Load Data were collected through a wearable inertial sensor (TalentPlayers TPDev, firmware version 1.3). To avoid interunit errors, each participant was assigned the same ISD for each OM. Among the available devices, TalentPlayers was chosen as it provides very similar data compared to traditional GPS systems (i.e., instantaneous speed and distance, change of directions, and metabolic data) and it is already used by various Italian soccer teams (<https://talentplayers.com> (accessed on 16 December 2016)). This ISD is a small wearable device integrating a six degrees of freedom MEMS inertial sensor, capable of providing real-time acceleration and rotation data along three orthogonal axes at a frequency of 100 Hz per channel. It is designed to be worn on the lower leg using an elastic band. The validity and reliability of the ISD have been previously reported (399). All data were acquired by the TalentPlayer mobile app (software version 1.0.7) and uploaded to the TalentPlayers cloud. Figure 3.7 reports the EL indicators used in this study.

Indicators	Type	Description (Unit of measure)
TD	Cinematic/volume	Total distance covered (m)
MS*	Cinematic/intensity	Maximum speed reached (even for <1 second)
N°INTACC*	Mechanical/volume	Number of intense accelerations >2 m/s ²
N°INTDEC*	Mechanical/volume	Number of intense decelerations >2 m/s ²
N°HSR*	Cinematic/volume	Number of High Intensity Running at >20 km/h
DHSR*	Cinematic/volume	Distance traveled at speed (>20 km/h) (m)
MP*	Metabolic/intensity	Metabolic Power ($w \cdot kg^{-1}$) was calculated by multiplying EC (in $J \cdot kg^{-1} \cdot m^{-1}$) by running speed (v ; in $m \cdot s^{-1}$) at any given moment (i.e., every 0.2 s): $P_{met} = EC \cdot v$. In order to assess metabolic power, considering the energy expenditure and derived, the equation developed by di Prampero et al. (2005). established on previously studies by Minetti et al. (2002). and Osgnach et al. (2010). was adopted. (Watt = w).
DHMP*	Metabolic/volume	Distance traveled in the metabolic power zone (20–35 w) (m)
DEMP*	Metabolic/volume	Distance traveled in the metabolic power zone (35–55 w) (m)
DMMP*	Metabolic/volume	Distance traveled in the metabolic power zone (>55 w) (m)
N°INTACC/ MIN	Mechanical/intensity	Number of intense accelerations >2 m/s ² per minute
N°INTDEC/ MIN	Mechanical/intensity	Number of intense decelerations >2 m/s ² per minute
DHSR/MIN	Cinematic/intensity	Distance traveled in the speed zone (>20 km/h) (m) per minute
N° HSR	Cinematic/volume	Number of runs at speed zone (>20 km/h) (m)

Note. Legend: TD, Total Distance; MS, Maximal Speed; N°INTACC, Number of accelerations; N°INTDEC, Number of decelerations; N°HSR, Number of High-Speed Running; WT, Walking Time; THSR; DHSR, Distance High-Speed Running; MP, Metabolic Power; TLMP, DHMP, Distance High Metabolic Power; DEMPP, Distance Elevated Metabolic Power; DMMP, Distance Max Metabolic Power; *Intensity indicator.

Fig. 3.7 Descriptions of the External Load indicators.

2.4. Data Analysis

2.4.1. Feature reduction

A principal component analysis (PCA) was used to reduce the feature dimension space in order to aggregate features to summarize the training workloads performed by soccer players during training and matches. PCA is a linear dimensionality reduction technique, which converts a set of correlated features in the high dimensional space into a series of uncorrelated features in the low dimensional space.

In particular, linear dimensionality reduction using Singular Value Decomposition (SVD) of the data was used to project the data to a lower dimensional space. To detect the best number of components the explained variance threshold was set at 90%. The input workload features were previously normalized between 0 and 1 to reduce intra-features variability. 0.2 was set as minimal limit for extracting features PCA scores. Sklearn python library was used for PCA analysis. Kaiser-Meyer-Olkin (KMO) Test was used to measure the suitability of data for factor analysis. It determines the adequacy for each observed variable and for the complete model. KMO estimates the proportion of variance among the entire observed variable. Lower proportion is more suitable for factor analysis. KMO values range between 0 and 1. Value of KMO less than 0.6 is considered inadequate.

2.4.2. Scores computation

The sum of the product between PCA weight of each component and the workload performed by a player in a specific training permit to create n independent workload values as showed in Equation 1:

$$PCA\ score_i = \sum_{f=0}^n w_{f_i} * x_f \quad (Eq. 1)$$

where i, f, w and x refer to the PCA component, the workload feature, the PCA weight and the workload value, respectively.

Due to the fact that, in accordance with the PCA weights and feature values, the PCA scores could be negative, the minimum possible value, i.e., when all the workload values are equal to 0, were added to all the PCA scores.

Based on the n PCA scores and the internal loads (expressed as rating of perceived exertion - RPE), 2 metrics were computed. In particular, one metric reflects the players performance (PERF - Equation 2), while the second one is focused on workload (WORK - Equation 3).

$$PERF = \frac{(PCA_i + \dots + PCA_n)/n}{RPE} \quad (Eq. 2)$$

$$WORK = \frac{PCA_i + \dots + PCA_n}{n} * RPE * duration \quad (Eq. 3)$$

2.4.3. Statistical analysis

The normality of data distribution was tested by Shapiro-Wilks' Normality test. Parametric or non-parametric statistical test was selected in accordance with the result of this test. Spearman Rho's correlation analysis (rs) was performed to identify relationships among scores. To meet any assumption for the correlation analysis, a repeated measure model with autoregressive approach (for time series analysis) was used. An autocorrelation analysis was conducted to detect similarity between

observations among the variable time series as a function of the time lag between them. Autocorrelation is the correlation of a signal with a delayed copy of itself as a function of delay. The analysis of autocorrelation is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal obscured by noise or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. In statistics, the autocorrelation of a real or complex random process is the Pearson correlation (r) between values of the process at different times, as a function of the two times or of the time lag. Two-way analysis of variance for repeated measures on two factors (two-way ANOVA RM) based on a linear mixed model was used to detect difference among MD and role. The first aim of this analysis is to detect interaction among MD and role. The interaction indicates different response of role in MDs. Moreover, difference among roles and among MDs were investigated. The analysis was conducted by Python 3.8 programming language.

3. RESULTS

Three main components were detected by PCA ($KMO = 0.82$). These components explained the 93.3% of the total variance among the multidimensional workloads space. The absolute values of the weights for each workload in each PCA component are provided in Figure 3.8. Based on these analyses, it is possible to define a name that describes the components as: i) volume metabolic related component, ii) intensity mechanical stimuli component, and iii) intensity metabolic/mechanical component.

The low Spearman Rho's correlation coefficients detected between PCA components indicate that these parameters were independent of each other and consequently provide different workload information. Similarly, also the two cumulative scores (i.e., PREF and WORK) were low correlated ($r_s = -0.20$) indicating that performance and workload scores were independent. Moreover, PERF showed a moderate correlation with "Intensity mechanical stimuli" component ($r_s = 0.46$), while WORK with "Volume metabolic related" and "Intensity metabolic/mechanical" components ($r_s = 0.63$ and $r_s = 0.34$, respectively) indicating that these components were the ones that most influence the cumulative scores.

The autocorrelation analysis showed a weekly microcycle in all the scores. A positive autocorrelation was detected every 7 days and multiple of 7 indicating that a similar pattern was repeated every 7 days. Moreover, a negative autocorrelation was found every 3-4 days denoting that an inverse trend

was performed in the middle of the training microcycle. These results were in line with the structure of the soccer training weekly microcycle (training-recovery balance).

Two-way ANOVA RM showed a statistical difference among MD and playing position for the three PCA components and PERF (Table 3.8). Even if there were differences in both MD and playing position, the trend of these scores among MD were similar in each playing position. Differently, a statistical interaction was detected for WORK (Table 3.8) showing a different trend among playing position in different MDs.

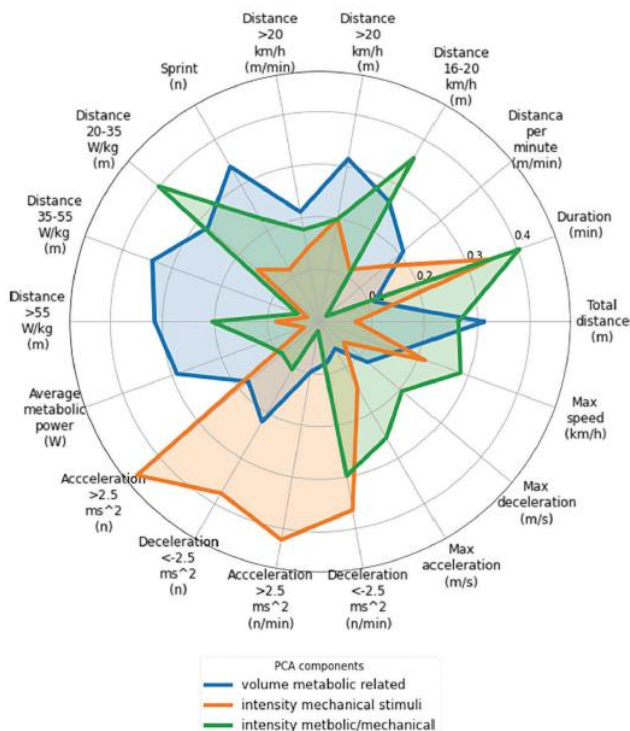


Figure 3.8. Absolute value for each workload feature in each PCA component. The higher the value the higher is the influence of a specific workload value on the PCA score computation.

Table 3.8. Descriptive statistics and statistical analysis of each score splitted by role and GD.

GD	role	volume metabolic related _b	intensity mechanical stimuli _{a,b}	intensity metabolic mechanical _{a,b}	PERF _b	WORK _{int}
2	CB	1.89 (0.27)	0.45 (0.20)	0.55 (0.32)	0.20 (0.06)	496.90 (153.40)

2	CM	2.22 (0.43)	0.42 (0.16)	0.31 (0.16)	0.20 (0.14)	577.02 (233.03)
2	ES	1.87 (0.42)	0.40 (0.18)	0.56 (0.26)	0.21 (0.08)	445.11 (166.22)
2	FB	1.84 (0.32)	0.45 (0.33)	0.60 (0.26)	0.17 (0.05)	531.90 (151.40)
2	S	1.87 (0.54)	0.43 (0.29)	0.47 (0.26)	0.16 (0.05)	529.01 (202.32)
2	WM	2.02 (0.59)	0.48 (0.28)	0.40 (0.28)	0.20 (0.08)	500.69 (205.07)
3	CB	1.85 (0.33)	0.64 (0.25)	0.34 (0.20)	0.18 (0.05)	577.87 (195.45)
3	CM	1.94 (0.35)	0.69 (0.22)	0.24 (0.14)	0.24 (0.09)	474.66 (176.04)
3	ES	1.91 (0.36)	0.71 (0.31)	0.24 (0.19)	0.21 (0.08)	531.83 (194.71)
3	FB	1.73 (0.32)	0.51 (0.31)	0.32 (0.12)	0.15 (0.04)	583.55 (214.50)
3	S	1.82 (0.25)	0.68 (0.23)	0.22 (0.14)	0.17 (0.03)	563.78 (166.43)
3	WM	1.86 (0.39)	0.80 (0.33)	0.22 (0.18)	0.27 (0.12)	429.10 (190.22)
4	CB	2.31 (0.54)	0.40 (0.29)	0.36 (0.22)	0.19 (0.06)	603.9 (180.10)
4	CM	2.27 (0.51)	0.50 (0.29)	0.24 (0.21)	0.20 (0.04)	524.59 (180.96)
4	ES	2.31 (0.49)	0.40 (0.27)	0.28 (0.18)	0.20 (0.05)	498.32 (154.13)
4	FB	2.43 (0.47)	0.47 (0.27)	0.28 (0.20)	0.16 (0.03)	680.49 (147.77)
4	S	2.45 (0.53)	0.39 (0.26)	0.20 (0.15)	0.18 (0.03)	550.29 (114.90)
4	WM	2.33 (0.50)	0.44 (0.25)	0.24 (0.20)	0.25 (0.09)	447.98 (210.56)
5	CB	1.58 (0.48)	0.51 (0.34)	0.32 (0.16)	0.18 (0.06)	399.02 (154.82)
5	CM	2.06 (0.29)	0.65 (0.20)	0.12 (0.09)	0.26 (0.06)	379.68 (129.71)
5	ES	1.94 (0.63)	0.48 (0.22)	0.19 (0.15)	0.23 (-0.11)	354.02 (198.40)
5	FB	1.67 (0.35)	0.30 (0.16)	0.32 (0.11)	0.17 (0.07)	391.23 (147.19)
5	S	1.58 (0.40)	0.39 (0.15)	0.17 (0.12)	0.20 (0.06)	289.18 (120.64)
5	WM	1.63 (0.37)	0.44 (0.20)	0.25 (0.13)	0.30 (0.12)	239.11 (112.14)
-1	CB	0.41 (0.35)	0.42 (0.23)	0.12 (0.06)	0.17 (0.08)	38.67 (21.54)
-1	CM	0.44 (0.09)	0.74 (0.33)	0.09 (0.07)	0.32 (0.17)	37.32 (14.43)
-1	ES	0.59 (0.36)	0.40 (0.26)	0.22 (0.13)	0.24 (0.20)	45.04 (24.35)
-1	FB	0.41 (0.21)	0.28 (0.21)	0.11 (0.10)	0.23 (0.16)	20.70 (8.04)
-1	S	0.36 (0.23)	0.41 (0.39)	0.16 (0.14)	0.24 (0.23)	26.15 (18.46)
-1	WM	0.21 (0.15)	0.31 (0.22)	0.06 (0.04)	0.15 (0.12)	16.61 (10.10)
0	CB	1.97 (0.57)	0.18 (0.15)	0.34 (0.19)	0.10 (0.02)	647.08 (288.79)
0	CM	1.61 (0.42)	0.12 (0.08)	0.19 (0.18)	0.12 (0.02)	282.11 (206.81)
0	ES	2.09 (0.54)	0.13 (0.10)	0.14 (0.10)	0.13 (0.02)	419.07 (241.04)
0	FB	2.00 (0.43)	0.13 (0.09)	0.24 (0.15)	0.11 (0.01)	516.86 (200.70)
0	S	2.29 (0.48)	0.14 (0.10)	0.11 (0.12)	0.10 (0.02)	625.62 (239.42)
0	WM	2.06 (0.42)	0.1 (0.09)	0.22 (0.13)	0.18 (0.05)	349.43 (160.45)

Two-way ANOVA statistical difference: a difference among role; b difference among GD; interaction between role and GD.

4. DISCUSSION

The main aim of this study was to create two Scores that allow to detect both individuals' physical performance and global TL (i.e., PERF and WORK scores, respectively) by using external and internal load indicators. The scores permit to analyse the microcycle workload by considering a singular indicator avoiding to control several indicators provided by MEMS devices facilitating the understanding of the workload behaviour especially for the technical staff. Based on the two computed score we found a statistical difference among MDs and playing position. The scores showed a similar MD pattern for each playing position. While a statistical interaction was found for WORK score showing a different trend among playing position in different MDs.

To calculate scores, three main components, that permits to assess different characteristics of the training workloads, have been obtained by PCA as: i) volume metabolic related component, ii) intensity mechanical stimuli component, and iii) intensity metabolic/mechanical component. The combination of these components and the internal load (RPE) allows us to compute the two scores in accordance with the aim of this study. The performance score (i.e., PERF) is computed as the ratio between external and internal load (EL/IL) (396). The use of this ratio to understand physical performance (i.e., athlete's fitness status) is supported by the works carried out by Gabbett and colleagues (385) and Impellizzeri et al. framework (387). Accordingly, some studies have implemented the EL/IL ratio to understand how an athlete responds to the administered load. For example, Derbidge et al. proposed three different ratios to assess the players' loads (i.e., total distance/HR exertion [HRe], player load/HRe, and equivalent distance/HRe) (396). Differently to the previous studies, we selected the EL indicators not arbitrarily, but by a data driven approach that permits creating more holistic and not human-biased external load indicators.

Concerning the attempt to calculate a global TL indicator, the WORK score has been computed considering EL, IL (i.e., based on RPE), and duration. The rationale behind the implementation of this score can be understood considering the TL framework (including both EL and IL) and can be operationalized following the exposure/dose–response function theory (i.e., a concept common in epidemiology that describes the relationship between the amounts of a factor/agent [i.e., dose] and the responses [e.g., risk of an outcome] (400-402)). In sports context, the theoretical dose–response function is explained by the parabola (or “inverted U” shape) where the performance improves with increases in TL up until a maximum level is reached, and outside this point, further increases in TL consequence in a worsening of performance (overreaching and overtraining). WORK score is

calculated in accordance with TL theory as the product of Duration (i.e., time) and Intensity (i.e., calculated as EL indicators reduced by PCA and RPE for internal load). Several studies have monitored the training/match load in soccer considering EL, IL, or both EL and IL (integrated approach) as suggested by Impellizzeri framework (387, 402). Noteworthy, no study has ever implemented a formula to obtain a global load that includes both EL (by selecting load indicators with complex analysis such as PCA) and IL. Moreover, many studies have used indicators derived from GPS or Inertial devices considering them as EL. Actually, in order to obtain the “external load”, the values detected by a given indicator (e.g., Total distance) has to be multiplied with match/training duration, as suggested by the TL framework carried out by Impellizzeri and Colleagues (387). However, since none of these external load indicators has been multiplied by the duration of a given exercise or of the entire training session/competition, it does not seem possible to be able to refer to the “TL concept” (i.e., EL). In fact, Coyne et al., (403) have recommended using the training impulse (the product of training volume and intensity factors) for IL and EL calculation, rather than a singular volume or intensity factor. This approach allows comparing “apples with apples” avoiding methodological differences among studies which could make comparisons difficult inducing possible misleading interpretation (403). The use of a data driven approach, i.e., PCA, is paramount to reduce the large amount of available indicators as more than one indicator should be considered to obtain a complete and appropriate view of the physical performance of the soccer players taking into consideration all the components of the EL (i.e., metabolic, speed-related and accelerations-related). Indeed, authors (387, 392, 402) highlighted that a lack of a “gold standard” to determine intensity in soccer makes explaining the intensity concept difficult and, consequently, making it difficult to select appropriate indicators to assess the soccer physical performance. In this way, practitioners should consider together different EL and IL indicators during the monitoring process because each of them explains a partial component of soccer physical performance. PCA selection allows the detection of EL indicators more appropriately than a subjective approach. Actually, our analysis shows a low correlation between PCA components that are independent of each other and consequently provide different information. Consequently, the two cumulative Scores (i.e., PREF and WORK) are low correlated ($r = -0.20$) indicating that performance and workload scores provide different information despite common measures of exposure (e.g., acute and chronic TL and their ratio) lack conceptual and computational validity (404).

In this study, PERF and WORK scores were used to evaluate the typical soccer physical performance and the microcycle workload considering also the different playing position. The timeseries analysis of the scores showed a weekly microcycle structure (i.e., a positive autocorrelation was detected every

7 days and multiple of 7 indicating that a similar pattern is repeated every 7 days). These results are in line with the structure of the soccer training weekly microcycle (training-recovery balance) (405-407). For example, Oliva-Lozano et al., (394) found a significant difference in load variability within the microcycle depending on the training day. Actually, previous studies have also showed that the TL decreases as the training day is closest (e.g., greater workload in -4MD or -3MD compared to -2MD or -1MD) (196, 408). However, to the best of the authors' knowledge, only Oliva-Lozano et al., (394) have analysed the load variability within the microcycle considering EL key indicators through PCA showing the lowest variability of all training days observed in -1MD (due to tapering strategies adopted by coaches) while the highest in +1MD (409). These results are corroborated by the current study that found the highest EL (based on scores) in MD+3 and MD+4 and the lowest one in MD-1.

One of the novel findings of our study was the investigation of the microcycle structure (i.e., MD system) load based on the new scores computed considering also playing position. Literature shows a different load for each playing position during training and competition (145, 389, 410, 411). In the same way, we have found a statistical difference among MD and among playing positions for the three PCA components and PERF score, but they follow the same training microcycle structure. Conversely, Nobari et al., (412), reported that the weekly TL changed throughout the season, although no significant differences were observed between playing positions. These results disagree with our finding and despite the trend of these scores across MDs was similar in each playing position, a statistical interaction was detected for WORK score showing a different trend among playing positions in different MDs (i.e., each playing position follows a well-defined WORK's microcycle). The study of TL is complex, and the conclusion should be contextualised to the sample examined. Several variables can contribute to determine the external and internal load such as, training status, methodology, level of competition and training typology. Indeed, studies should deeply provide specific information about training (e.g., training type, recovery strategies, athlete fitness status) to better understand the athlete's physiological and perception responses to training (i.e., internal load) as showed by previous studies on RPE (413).

5. CONCLUSION

This study aimed to create two scores from external and internal load indicators to assess both individuals' physical performance (i.e., PERF score) and global training workload (i.e., WORK score). PCA has provided three different characteristics of the training external workloads (i.e., i) volume metabolic related component, ii) intensity mechanical stimuli component, and iii) intensity metabolic/mechanical component). The combination of these components and the internal load (RPE) allows us to compute the two scores. The Performance score (i.e., PERF) is computed as the ratio between external and internal load (EL/IL), while the Work score has been computed considering EL, IL (i.e., based on RPE), and duration. Moreover, a weekly microcycle structure has been provided through the timeseries analysis showing that a pattern is repeated every 7 days for both scores. Also, by analysing the scores across MDs, a similar result in each playing position have been found, although the WORK score shows a different trend among playing positions in different MDs (i.e., each playing position present a well-defined WORK's microcycle).

This paper would like to propose an innovative approach to assess both the players' physical performance and TL by using a machine learning approach that permits to reduce a large dataset considering the main external load indicators in an objective way. The main strength of this work is the use of the Performance and Workload scores to monitor training and soccer matches by including the main external load indicators, the players' physiological responses (i.e., internal load) and duration. Our approach allows to assess the overall training/match load and players' performance considering only two indicators against numerous indicators that could be redundant and selected based on the subjective choices of the practitioners. This study presents some limitations. Data has been collected in young male professional soccer players with a number of both training and matches observed within August and February. Accordingly, care should be taken when generalizing these findings due to the relatively limited number of observations in the total sample. Despite several external load indicators have been included in our analysis, the variables related to speed and acceleration as well as metabolic power were set on absolute thresholds (e.g., distance >20 Km/h for high-speed running), and other metric with different thresholds could have been included. In this regard, future studies may consider the addition of individualized zones based on maximum speed or maximum acceleration capacities. Several external (environmental) and internal factors (psychological, stress, sleep, fatigue) could affect the physical performance during matches and training. For example, the tactical requirements of coaches (e.g., 1-4-3-3 vs -1-3-5-2 system) determine different external load responses. Future studies should include a larger sample, including other levels of competition, tactical requirement, as well as other sports to strength the power of PCA analysis. Although the Score aiming to synthetized both physical performance and training load useful

for coaches, given the fundamental contribution (with unique and specific meaning and information) provided by each external and internal load indicators, the monitoring process should include both Scores and both external and internal load indicators for more in-depth analysis.

6. PRACTICAL APPLICATION

The machine learning approach conducted in this study provides valuable information on training/match load and players physical performance and relative playing position in the microcycle structure (i.e., MD system) based on the two computed scores. As a matter of fact, in order to describe the players' physical performance and workload during training and matches two scores have been computed from EL and IL data. Actually, the approach used in this work allows practitioners to better identify the workloads performed by players during training microcycle or official match along with player's performance. Since practitioners should consider together different EL and IL indicators during the monitoring process because each of them explains a partial component of soccer physical performance, PCA analysis allows the detection of EL indicators more appropriately than a subjective approach. In detail, this approach permits to detect relevant information from load and performance. Therefore, it is possible to understand the differences between training and official matches or between MDs, considering also each player's playing position. In this way, practitioners could prescribe the training drill in the microcycle considering the results provided by two scores.

3.4 Machine Learning Analysis of Intensity Profiles and Key Indicators in Standard Microcycle of Professional Soccer Players

Guglielmo Pillitteri, Rabi Muazu Musa, Filipe Manuel Clemente, Tindaro Bongiovanni, Marco Petrucci, Antonino Bianco, Marco Beato and Giuseppe Battaglia – Journal of strength and Conditioning research (2025)

Introduction

Monitoring and managing training load (TL) have been widely investigated in sports science, particularly in the context of soccer microcycle planning (8, 33) aiming to optimizing player's physical performance while reducing injury risks. TL has been defined as a higher-order construct

reflecting the amount of physical training that the athletes do and experience, considering the physiological and mechanical stresses athletes experience during training (30).

As a multidimensional construct, it has been conceptually quantified using indicators of external (EL) and IL (IL) (17, 30). IL reflects the athlete's physiological response, such as perceived exertion, while EL can be quantified through electronic performance and tracking systems, which include camera-based and wearable technologies such as global navigation satellite systems (GNSS), which enable the tracking of player activities including distances in different velocity zones and events related with changes in velocity (e.g., accelerations and decelerations) (414).

A microcycle typically spans a week and involves a structured sequence of training sessions aimed at optimizing performance and recovery (7, 415). Understanding how TL interact within a microcycle is crucial for maximizing physical performance while possibly reducing the risk of injuries. Several articles have been focused on TL management within soccer microcycle (7, 87, 416). A recent systematic review (416) focused on TL management in soccer players during a typical microcycle week and it shows that the three days before match day (MD-3) typically imposes the highest physical demands. This is true for activities like high-speed running and total distance covered while training sessions immediately before and after matches (MD-1) emphasize recovery and tapering to maintain players' readiness and avoid overloading. Middle-of-the-week sessions (MD-4, MD-3) are designed for higher-intensity training to build physical capacities and Match Day (MD) is the most physically demanding session of the week, particularly for players in starting positions. Indeed, Non-starters often experience compensatory sessions to replicate match intensity (271).

Several studies (81, 201, 416-419) have examined the impact of TL on the microcycle in soccer, offering valuable insights for practitioners. While these studies have produced promising results, they have primarily relied on traditional statistical analyses to manage large datasets, revealing a gap in the analytical approaches employed. However, a more suitable analytical approach is needed to account for multidimensional factors (11, 137, 420, 421). For this reason, we evidenced a gap in literature concerning the traditional analysis applied in these studies. For example, a study (419) has compared the EL on specific MD sessions and playing positions during congested fixtures in elite football through a linear mixed model. Authors found that HSR and HMLD distances were higher on MD+1 and MD-2 compared to both MD-1 sessions (416). Additionally, training loads were generally evenly distributed across playing positions, except for fullbacks, who covered more HSR distance than centre-backs, and midfielders, who reported higher RPE values compared to defensive midfielders and fullbacks.

Recent advancements in Machine Learning (ML) have opened new opportunities for more sophisticated analyses of TL data (11). The ability of ML to handle complex relationships and large

datasets makes it an ideal tool for investigating how TL parameters interact with physical performance across different days of the microcycle (10, 421). This type of analysis may help coaches and sports scientists aiming to optimize training programs and enhance performance. Despite the growing body of research on TL and its relationship to training outcomes (74, 81, 416, 419, 422-424), there is a notable gap in the application of ML techniques to study TL, particularly in relation to match days intensity within a standard microcycle (11, 421). Few studies have employed ML approaches to examine TL within this context, and those that do often focus on broad external and IL indicators without delving into the intensity component for specific MD types. For example, Pillitteri et al. (87) explored the microcycle structure by examining time-series data of external and IL scores, revealing a recurring pattern every 7 days (i.e., MD-7), but they did not analyse the intensity variation across specific MD types (e.g., MD-3) or use ML techniques for a deeper understanding of these relationships. Thus, while some foundational work has been done, there remains a clear gap in how TL intensity, especially on different MD typologies including different among playing position, can be analysed using ML methods.

ML offers a powerful solution by enabling the analysis of large, multidimensional datasets, identifying hidden patterns, and uncovering interactions that may be overlooked with conventional approaches (11, 14, 420, 425). By leveraging ML, it may become possible to model the dynamic nature of training load, account for positional differences in physical demands, and predict performance outcomes with greater accuracy (262). This approach not only enhances the understanding of how TL fluctuates throughout a standard microcycle but also provides data-driven insights to support individualized training prescriptions tailored to the specific needs of each playing position. Therefore, this study aims to bridge this gap by providing a detailed, ML-based analysis of TL intensity across different MD types within a standard microcycle. The study's objectives are: 1) to identify intensity profiles (low-medium-high) for various MD types and playing position using ML techniques; 2) to establish a comprehensive benchmark for both external and IL intensity indicators for each MD type within a standard microcycle; 3) to predict intensity variations across different MD types based on internal and EL variables using ML techniques; 4) to identify key parameters—both internal and external—that contribute most significantly to model performance and 5) to analyse how playing positions influence internal and EL parameters for each MD type.

Methods

Experimental Approach to the Problem

In this cohort longitudinal study, the external training workloads of twenty-nine-professional Italian soccer players were monitored by using a GNSS, respectively, during the competitive season from July to June (2023-2024). Soccer players were categorized into six groups according to their role as follows: central backs (CB), wide strikers (WS), fullback (FB), midfielder (MDF), wide midfielder (WM) and central strikers (CS). A standard microcycle includes 5 training session, 1 recovery day a 1 match day/MD. The following MD type have been considered (n = number of observation): MD+2 (n = 441), MD+3 (n = 377), MD-3 (n = 237), MD-2 (n = 249), MD-1 (n = 320), MD (n = 580). Moreover, the number of players per playing position is CB (n =475), central MDF (n =216), CS (n =322), FB (n =371), wide MDF (n =437) and WS (n =383). The data collected by GNSS from 91 training sessions and 38 official match and were categorized as Match Day (MD), MD+2 (2 day after the match), MD+3 (3 day after the match), MD-3 (3 days prior to the match), MD-2 (2 days prior to the match), MD-1 (1 day prior to the match).

Subjects

The following inclusion criteria were considered: 1) professional male soccer players; 2) no injury in the previous six months; Players who participated in the entire training session.

Based on the exclusion criteria, only the goalkeepers were not eligible for the study. The duration of the training sessions was approximately 72 min and mainly included technical-tactical team drills along with some general physical exercise without ball (e.g., high intensity interval training, HIIT). Strength and conditioning exercises were performed twice a week (i.e., two sessions in the gym (main/power)). Twenty-nine-professional soccer players (age: 25.9 ± 4.2 years, height: 182.1 ± 5.9 cm, body mass: 84.3 ± 21.8 Kg) competing in the Italian Serie B championship were analysed (Tier 4 in the Participants Classification Framework). In detail, 2204 observations, (194 ± 76 , min=40, max=322 for each player), (91 training session and 38 Official Matches) have been assessed monitoring EL. Participants' playing positions were the following: CB, n = 5; FB, n = 5; MD, n = 3; WM, n = 7, WS, n = 5, and CS, n = 4. All participants signed an informed consent before taking part in the data collection. The Bioethics Committee of the University of Palermo (n. 68/2021) approved the study, which complies with the principles of the Declaration of Helsinki.

Procedures

Participants were monitored during both training and official matches performed on a natural grass pitch during the 2023-2024 season. All players performed a typical 25-minute pre-match warm-up before OM and 30' before training (15' specific pre-activation in the gym and 10' on field specific-preparation warm-up).

IL data was collected through the session-RPE (CR10) method by Foster et al. (243), 30 min after each session or official match by specialized coach; the duration (minutes) and each RPE training session were recorded in a daily routine. Training Load (TL) for each participant was calculated from the product of the session duration and the player's RPE (231, 243). The training session duration included warm up, cool down and rest between tasks.

EL Data were collected through a Global navigation satellite systems Apex (STATSports, Northern Ireland, Newry) with the following characteristics: wide 53 mm, high 58 mm, and mass 548 g. The 10 Hz GNSS device is equipped with a 100 Hz gyroscope, a 100 Hz triaxial accelerometer, and a 10 Hz magnetometer and HR sensor (426, 427). Apex data were downloaded and further analyzed by the respective software (Apex 10 Hz, Sonra v4.2.1). Each participant was assigned the same GNSS for each OM and training session to avoid interunit errors. The validity and reliability of the GNSS have been previously reported (426-428). Specifically, validity during linear and sport specific activities was previously demonstrated (428). Apex units have excellent interunit reliability and a coefficient of variation ranging from 1.64 to 2.91% for the analysis of peak speed during short sprints (between 5 and 30 m) (429). Very recently, the interunit reliability was analysed during a standardised intermittent running protocol, which showed high reliability scores for nearly all metrics analysed (426). The GNSS device was started 15 minutes prior to the assessment to make available the acquisition of satellite signals. The satellites connected to each unit ranged between 18 and 21 while the average horizontal dilution of precision (HDOP) was 0.8 (381, 428).

A microcycle refers to the period between two official matches (MD). A Standard microcycle includes 7 days (6 training sessions and 1 official match). The standard microcycle begins the day after an official match (MD+1/-6). Standard microcycle includes: Match Day (MD), MD+1/-6 (1 day after the match/ 6 days prior to the match), MD+2/-5 (2 day after the match/ 5 days prior to the match), MD+3/-4 (3 day after the match/ 4 days prior to the match), MD+4/-3 (4 day after the match/ 3 days prior to the match), MD+5/-2 (5 day after the match/ 2 days prior to the match), MD+6/-1 (6 day after the match/ 1 days prior to the match). Table 1 supplementary) provides a detailed example of a soccer training program within a standard microcycle for professional players.

Statistical Analyses

Data Treatment

The data on the internal and EL parameters were gathered and pre-processed. The data were also normalized using min-max scaling to avoid bias from different units of measurement (430). This normalization technique ensures that all variables contribute equally to the analysis, preventing any single parameter with larger numerical values from dominating the model. The dataset included IL parameters (RPE) and EL parameters (session duration, accelerations/min ($>3\text{m}\cdot\text{s}^2$), Mechanicalwork/min, decelerations/min ($>-3\text{m}\cdot\text{s}^2$), total distance/min, distance 0-7 Km/h/min, distance >14.4 Km/min, distance >19.8 Km/h/min, distance >25.2 Km/h/min, maxSpeed.) for analysis. If a player missed a training session, their data for that session were not included in the analysis; this ensures transparency regarding how absences were managed and how they may have influenced the dataset.

Our purpose is to investigate whether these internal and ELs indicators could predict the MD type (e.g., MD-3) intensity of the players using a lightGBM-based ML model (11). By standardizing the data and including a comprehensive set of load parameters, we aimed to develop a robust predictive model that can provide valuable insights into the factors influencing the intensity profiles of the players. The PyCaret libraries were utilized for the development of the LGBM model via the Spyder Integrated Development Environment (IDE). Other statistical analyses were conducted via Jamovi version 2.4.14.

Clustering Analysis for Determining Intensity Profile

We employed an unsupervised machine learning model, specifically k-means clustering, to categorize (n) observations into (k) clusters based on internal and external parameters (11). Each observation was assigned to the cluster with the nearest centroid. To determine the optimal number of clusters for all MD type, we conducted a silhouette analysis using the k-means model. Finally, we examined the variations in intensity profiles across different player positions.

Determining Intensity Profile

We employed an unsupervised machine learning model, specifically k-means clustering, to categorize (n) observations into (k) clusters based on internal and external parameters. Each observation was assigned to the cluster with the nearest centroid. To determine the optimal number

of clusters for all MD type, we conducted a silhouette analysis using the k-means model. Finally, we examined the variations in intensity profiles across different player positions.

MD Types Prediction

Rationale and Development Process of the LGBM Model

The LightGBM (Light Gradient Boosting Machine) model is a sophisticated gradient-boosting framework that utilizes a leaf-wise tree growth strategy. This approach prioritises splitting leaves with the largest loss reduction, resulting in models that are both more accurate and efficient compared to traditional tree-based algorithms. LightGBM incorporates innovative techniques such as Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB), which further enhance training speed and reduce memory usage. These features make the algorithm particularly well-suited for handling large datasets with numerous features (431). Consequently, LightGBM is a powerful tool for predictive modelling across various domains, including sports science, where it is essential to manage complex datasets and generate real-time predictions. This capability underpins the rationale for selecting LightGBM to predict different MD type in relation to internal and external variables within a standard microcycle.

We employed five-fold stratified cross-validation to prevent overfitting, splitting the dataset into five distinct folds for testing (432-434). Wherein the data comprising 2204 observations was divided using a holdout approach. Specifically, 70% of the data (1543 observations) was allocated for training and validation, with 1080 observations used for training and 463 observations held out for validation. The remaining 661 unseen observations, which were not exposed to the model during training, were reserved for independent testing. The stratified 5-fold hold-out cross-validation technique was chosen over the typical 70-30 split with standard k-fold cross-validation to ensure that the training and validation sets were representative of the entire dataset, particularly with respect to class distribution. This approach helps to mitigate the risk of data imbalance, which can be critical in smaller datasets (420, 435). Moreover, by reserving a separate independent test set, we aimed to provide a more robust evaluation of the model's generalization capability on completely unseen data. Additionally, we conducted a sensitivity analysis using the feature importance technique to identify internal and external-related parameters that have a higher contribution towards model accuracy.

Model Evaluation Metrics

To evaluate the efficacy of the developed model, various performance metrics were utilized, including classification accuracy (ACC), area under the curve (AUC), recall, precision (PREC), F1 score, Kappa, and Matthew's correlation coefficient (MCC) (10, 436). These metrics provided a comprehensive assessment of the model's performance across different dimensions: ACC represents the proportion of correct predictions (both true positives and true negatives) among the total number of cases, offering a general measure of the model's overall effectiveness. AUC measures the area under the Receiver Operating Characteristic (ROC) curve, which plots the true positive rate against the false positive rate at various threshold settings, indicating the model's ability to discriminate between positive and negative classes. Recall refers to the proportion of true positive predictions among all actual positive cases (sensitivity), reflecting the model's ability to identify all relevant positive cases. Precision is the proportion of true positive predictions among all positive predictions made by the model, indicating the accuracy of the positive predictions. The F1 score reflects the harmonic mean of precision and recall, providing a single metric that balances both, especially useful for imbalanced class distributions. Kappa is a statistical measure of inter-rater agreement for categorical items, adjusted for agreement occurring by chance, evaluating the degree of agreement between predicted and actual classifications (10). MCC measures the correlation coefficient between observed and predicted binary classifications, ranging from -1 to +1, offering a balanced measure that considers true and false positives and negatives, even in the case of class imbalance (436). These metrics collectively offer a comprehensive evaluation of the model's performance, highlighting its strengths and weaknesses.

Feature Importance Investigation

Significant attribute evaluation was used to investigate the external and IL parameters that have a higher influence on the model performance. This technique was chosen because it effectively measures the relevance of each attribute by accounting for the mutual information between attributes and the target variable, thus providing a balanced assessment of both linear and non-linear relationships within the dataset (437, 438). By identifying the most influential variables, this method helps highlight the most important parameters that significantly impact performance, thereby enhancing model interpretability and predictive power.

Analysis of MD types Across Different Playing Positions

A two-way mixed-design ANOVA was conducted to examine the effects of playing MD types and playing position on the various external and IL parameters indicated as significant via the features importance analysis. Playing position was a between-subjects factor, and MD types was a within-subjects factor. This design allowed for the assessment of both main effects (the individual influence

of playing position and MD types) and the interaction effect (how the effect of MD types varies across different playing positions). Where Mauchly's Test of Sphericity indicated that the assumption of sphericity had been violated, the Greenhouse-Geisser correction was applied to adjust the degrees of freedom. Significant interaction effects were further analysed using post-hoc comparisons with a Tukey correction to control for multiple comparisons (439). An alpha level of .05 was used to determine statistical significance for the post-hoc tests. Figures were generated to visualize significant interactions and illustrate trends in the data.

Results

MD Types Prediction

Table 3.9 presents the descriptive statistics of the investigated parameters, including internal and EL parameters across different MD types, playing positions and their corresponding counts, means, medians, standard deviations as well as minimum and maximum scores. Notably, player physical performance, as reflected by the investigated parameters, varies across these MD types.

Table 3.9 Descriptive statistics of the study parameters

Parameters	MD type	Playing Position	N	Mean	Median	SD	Minimum	Maximum
sessionDuration (min)	MD	central back	100	87.75	97.00	25.10	13.00	135.00
		central midfielder	59	71.70	79.00	30.15	5.00	113.00
		central strikers	94	57.62	59.00	32.49	5.00	113.00
		fullback	103	69.75	78.00	30.92	8.00	135.00
		wide midfielder	117	56.66	60.00	28.65	5.00	102.00
		wide strikers	107	57.35	60.00	27.13	3.00	102.00
	MD+2	central back	103	73.27	70.00	19.20	36.00	120.00
		central midfielder	43	72.79	72.00	20.03	36.00	120.00
		central strikers	64	76.75	81.50	18.35	36.00	120.00
		fullback	72	74.96	76.00	20.80	20.00	120.00
		wide midfielder	85	74.24	72.00	18.21	36.00	120.00
		wide strikers	74	74.30	76.00	18.66	36.00	120.00

RPE (AU)	MD+3	central back	88	79.63	82.00	12.62	50.00	100.00
		central midfielder	36	76.92	81.00	16.84	30.00	100.00
		central strikers	52	82.56	87.00	11.27	45.00	100.00
		fullback	60	81.07	82.00	11.88	45.00	100.00
		wide midfielder	77	80.40	80.00	11.48	45.00	100.00
		wide strikers	64	79.27	80.00	13.92	35.00	100.00
	MD-1	central back	73	63.15	65.00	9.85	45.00	80.00
		central midfielder	31	63.74	65.00	9.73	45.00	80.00
		central strikers	44	65.39	66.00	9.46	45.00	80.00
		fullback	55	64.47	66.00	10.25	45.00	80.00
		wide midfielder	64	64.64	66.00	9.71	45.00	80.00
		wide strikers	53	64.79	66.00	9.46	45.00	80.00
	MD-2	central back	56	74.43	78.00	13.97	40.00	100.00
		central midfielder	25	77.20	80.00	14.84	40.00	100.00
		central strikers	35	78.91	78.00	12.43	40.00	100.00
		fullback	41	77.42	78.00	12.33	55.00	100.00
		wide midfielder	48	79.17	79.00	12.57	55.00	100.00
		wide strikers	44	78.23	78.00	12.27	55.00	100.00
	MD-3	central back	55	73.96	73.00	15.96	35.00	108.00
		central midfielder	22	74.64	76.50	16.90	30.00	108.00
		central strikers	33	79.33	80.00	15.13	45.00	108.00
		fullback	40	75.90	73.00	14.30	54.00	108.00
		wide midfielder	46	74.96	73.00	12.91	50.00	108.00
		wide strikers	41	77.20	80.00	14.18	50.00	108.00
	MD	central back	100	6.67	7.00	1.93	1.00	9.50
		central midfielder	59	6.26	7.00	1.79	2.00	10.00
		central strikers	94	5.28	5.00	1.88	2.00	9.00
		fullback	103	6.36	7.00	2.22	2.00	10.00
		wide midfielder	117	5.30	5.00	2.13	1.00	9.00
		wide strikers	107	5.41	5.00	1.92	2.00	9.00

	central back	103	4.18	4.00	0.94	2.00	7.00
	central midfielder	43	4.69	5.00	1.18	2.00	9.00
MD+2	central strikers	64	4.59	4.50	1.03	2.00	8.50
	fullback	72	4.24	4.50	1.38	1.00	7.00
	wide midfielder	85	4.13	4.00	1.28	2.00	7.50
	wide strikers	74	4.42	4.00	1.24	1.00	8.00
	central back	88	4.12	4.00	1.10	1.00	6.00
	central midfielder	36	4.32	5.00	1.31	1.00	6.00
MD+3	central strikers	52	4.44	4.50	1.12	1.00	8.00
	fullback	60	4.60	4.50	1.32	2.00	8.00
	wide midfielder	77	4.21	4.00	1.19	1.00	8.00
	wide strikers	64	4.52	5.00	1.32	1.00	7.00
	central back	73	2.42	2.00	0.95	1.00	8.00
	central midfielder	31	2.31	2.00	0.69	1.00	4.50
MD-1	central strikers	44	2.31	2.00	0.73	1.00	4.00
	fullback	55	2.21	2.00	0.71	1.00	5.50
	wide midfielder	64	2.33	2.00	0.82	1.00	5.00
	wide strikers	53	2.28	2.00	0.81	1.00	7.00
	central back	56	2.77	3.00	0.76	1.00	4.50
	central midfielder	25	3.06	3.00	0.99	1.00	5.00
MD-2	central strikers	35	3.06	3.00	0.65	2.00	4.00
	fullback	41	3.13	3.00	1.23	1.00	8.50
	wide midfielder	48	3.15	3.00	0.99	1.00	5.50
	wide strikers	44	3.17	3.00	1.27	1.00	9.00
	central back	55	3.76	4.00	1.12	1.00	6.00
	central midfielder	22	4.30	5.00	1.10	1.00	6.00
MD-3	central strikers	33	4.46	4.50	0.80	2.00	6.00
	fullback	40	3.94	4.00	1.43	1.00	8.00
	wide midfielder	46	4.40	5.00	1.06	2.00	6.00
	wide strikers	41	4.29	4.00	1.05	2.00	6.50

accelerations/min	MD	central back	100	0.71	0.71	0.23	0.25	1.77
		central midfielder	59	0.72	0.71	0.14	0.45	1.18
		central strikers	94	0.72	0.69	0.22	0.35	1.71
		fullback	103	0.81	0.78	0.19	0.43	1.52
		wide midfielder	117	0.71	0.69	0.18	0.33	1.27
		wide strikers	107	0.77	0.75	0.25	0.06	1.80
	MD+2	central back	103	1.19	1.21	0.36	0.51	2.61
		central midfielder	43	1.12	1.06	0.39	0.36	2.42
		central strikers	64	1.11	1.08	0.32	0.64	2.27
		fullback	72	1.26	1.28	0.37	0.53	2.55
		wide midfielder	85	1.16	1.17	0.34	0.47	2.01
		wide strikers	74	1.22	1.19	0.36	0.48	2.06
	MD+3	central back	88	1.14	1.17	0.41	0.16	2.16
		central midfielder	36	1.01	1.03	0.33	0.38	1.75
		central strikers	52	1.01	1.04	0.31	0.32	1.53
		fullback	60	1.32	1.26	0.53	0.47	2.51
		wide midfielder	77	1.15	1.18	0.34	0.35	2.03
		wide strikers	64	1.13	1.10	0.43	0.47	2.16
	MD-1	central back	73	0.95	0.92	0.25	0.49	2.13
		central midfielder	31	0.84	0.82	0.24	0.47	1.54
		central strikers	44	0.77	0.75	0.17	0.42	1.26
		fullback	55	0.95	0.96	0.32	0.28	1.70
		wide midfielder	64	0.85	0.83	0.29	0.24	1.82
		wide strikers	53	0.92	0.90	0.30	0.48	1.61
	MD-2	central back	56	0.79	0.80	0.30	0.06	1.50
		central midfielder	25	0.81	0.83	0.21	0.28	1.15
		central strikers	35	0.71	0.70	0.23	0.17	1.06
		fullback	41	0.87	0.91	0.25	0.28	1.51
		wide midfielder	48	0.80	0.82	0.26	0.23	1.49
		wide strikers	44	0.88	0.87	0.28	0.25	1.78

Mechanicalwork/min	MD-3	central back	55	0.76	0.76	0.27	0.22	1.70
		central midfielder	22	0.89	0.83	0.34	0.57	2.16
		central strikers	33	0.72	0.70	0.17	0.44	1.22
		fullback	40	0.85	0.83	0.23	0.42	1.37
		wide midfielder	46	0.71	0.70	0.20	0.39	1.15
		wide strikers	41	0.82	0.80	0.21	0.48	1.26
	MD	central back	100	1.50	1.50	0.42	0.68	3.21
		central midfielder	59	1.51	1.52	0.24	0.95	2.14
		central strikers	94	1.49	1.47	0.31	0.95	2.42
		fullback	103	1.78	1.74	0.34	0.76	2.63
		wide midfielder	117	1.65	1.62	0.30	1.12	2.59
		wide strikers	107	1.75	1.73	0.38	0.86	3.40
	MD+2	central back	103	1.96	1.77	0.71	0.55	3.78
		central midfielder	43	1.93	1.85	0.57	0.83	3.48
		central strikers	64	1.79	1.72	0.61	0.82	3.19
		fullback	72	2.14	1.99	0.64	0.97	3.72
		wide midfielder	85	1.93	1.87	0.62	0.76	3.37
		wide strikers	74	1.94	1.76	0.64	0.73	3.57
	MD+3	central back	88	2.18	2.25	0.85	0.43	4.19
		central midfielder	36	2.07	2.03	0.90	0.75	5.32
		central strikers	52	1.88	1.91	0.63	0.48	3.14
		fullback	60	2.57	2.42	1.13	0.71	5.06
		wide midfielder	77	2.17	2.25	0.74	0.52	3.82
		wide strikers	64	2.21	2.23	0.77	0.59	4.10
	MD-1	central back	73	1.69	1.70	0.48	0.80	2.98
		central midfielder	31	1.49	1.47	0.41	0.43	2.25
		central strikers	44	1.37	1.34	0.41	0.66	2.82
		fullback	55	1.83	1.89	0.62	0.55	3.30
		wide midfielder	64	1.65	1.70	0.48	0.58	3.00
		wide strikers	53	1.62	1.61	0.50	0.44	2.60

Decelerations/min	MD-2	central back	56	1.35	1.35	0.49	0.09	2.06
		central midfielder	25	1.42	1.45	0.40	0.52	2.02
		central strikers	35	1.25	1.28	0.40	0.27	1.97
		fullback	41	1.55	1.56	0.52	0.44	2.72
		wide midfielder	48	1.41	1.40	0.44	0.42	2.37
		wide strikers	44	1.51	1.56	0.46	0.51	2.35
	MD-3	central back	55	1.43	1.36	0.53	0.42	2.88
		central midfielder	22	1.52	1.52	0.31	0.89	2.05
		central strikers	33	1.33	1.29	0.34	0.76	2.29
		fullback	40	1.57	1.54	0.44	0.72	2.83
		wide midfielder	46	1.47	1.40	0.44	0.70	2.98
		wide strikers	41	1.55	1.45	0.51	0.67	3.09
	MD	central back	100	0.78	0.78	0.21	0.33	1.46
		central midfielder	59	0.80	0.82	0.17	0.31	1.21
		central strikers	94	0.78	0.76	0.20	0.15	1.41
		fullback	103	0.98	0.96	0.19	0.57	1.57
		wide midfielder	117	0.94	0.93	0.18	0.61	1.40
		wide strikers	107	0.96	0.96	0.19	0.46	1.60
	MD+2	central back	103	0.76	0.64	0.41	0.03	2.09
		central midfielder	43	0.75	0.74	0.34	0.10	1.39
		central strikers	64	0.69	0.71	0.37	0.07	1.70
		fullback	72	0.86	0.84	0.43	0.00	1.77
		wide midfielder	85	0.76	0.76	0.40	0.04	1.59
		wide strikers	74	0.73	0.76	0.38	0.02	1.59
	MD+3	central back	88	1.04	1.05	0.47	0.18	2.09
		central midfielder	36	1.02	1.12	0.42	0.21	1.75
		central strikers	52	0.89	0.86	0.36	0.15	1.69
		fullback	60	1.28	1.20	0.64	0.24	2.55
		wide midfielder	77	1.06	1.12	0.43	0.16	1.92
		wide strikers	64	1.07	1.11	0.43	0.36	2.23

distanceTotal/min	MD-1	central back	73	0.74	0.77	0.25	0.22	1.20
		central midfielder	31	0.74	0.72	0.24	0.30	1.20
		central strikers	44	0.60	0.56	0.26	0.18	1.56
		fullback	55	0.90	0.92	0.36	0.25	1.64
		wide midfielder	64	0.82	0.82	0.29	0.26	1.38
		wide strikers	53	0.71	0.66	0.24	0.20	1.17
	MD-2	central back	56	0.61	0.59	0.29	0.03	1.64
		central midfielder	25	0.60	0.60	0.22	0.17	1.16
		central strikers	35	0.54	0.52	0.21	0.11	1.01
		fullback	41	0.67	0.68	0.29	0.16	1.29
		wide midfielder	48	0.60	0.62	0.22	0.19	1.13
		wide strikers	44	0.72	0.72	0.30	0.20	1.70
	MD-3	central back	55	0.64	0.59	0.30	0.17	1.90
		central midfielder	22	0.73	0.75	0.25	0.29	1.37
		central strikers	33	0.62	0.57	0.25	0.28	1.45
		fullback	40	0.73	0.69	0.23	0.30	1.36
		wide midfielder	46	0.67	0.72	0.22	0.30	1.16
		wide strikers	41	0.69	0.64	0.35	0.31	2.55
	MD	central back	100	98.27	98.93	9.16	47.09	116.51
		central midfielder	59	106.30	106.16	8.23	90.51	123.38
		central strikers	94	100.90	101.51	13.34	75.06	125.92
		fullback	103	108.62	108.15	8.24	87.25	134.14
		wide midfielder	117	115.31	115.61	8.30	84.76	134.43
		wide strikers	107	111.51	112.15	9.57	81.35	131.54
	MD+2	central back	103	108.43	114.62	18.45	48.50	139.28
		central midfielder	43	108.79	111.45	15.78	67.33	133.68
		central strikers	64	108.47	111.12	13.97	65.12	139.14
		fullback	72	111.79	115.25	19.22	39.07	173.77
		wide midfielder	85	115.39	119.57	19.59	53.93	177.25
		wide strikers	74	110.11	114.18	17.24	41.30	140.44

distance 0-7 Km/h/min	MD+3	central back	88	101.97	102.75	15.12	58.17	127.37
		central midfielder	36	97.80	100.35	17.32	58.67	130.19
		central strikers	52	95.87	97.13	15.97	50.87	128.14
		fullback	60	102.91	103.03	18.26	54.07	129.68
		wide midfielder	77	109.44	112.96	16.61	59.75	135.91
		wide strikers	64	102.36	105.73	18.95	39.93	167.57
	MD-1	central back	73	88.12	82.41	28.31	49.85	234.18
		central midfielder	31	82.41	81.59	11.44	62.34	113.03
		central strikers	44	75.93	73.55	13.50	53.72	115.51
		fullback	55	84.82	83.79	12.70	59.26	124.68
		wide midfielder	64	85.87	83.60	11.15	63.78	121.81
		wide strikers	53	81.56	81.06	11.64	58.95	121.54
	MD-2	central back	56	74.67	71.50	12.44	52.72	111.22
		central midfielder	25	74.88	71.00	9.59	62.01	97.07
		central strikers	35	70.15	69.56	8.68	54.33	94.53
		fullback	41	76.68	75.95	11.96	59.26	116.17
		wide midfielder	48	79.82	76.64	10.83	65.42	113.06
		wide strikers	44	80.46	74.26	15.05	54.36	135.04
	MD-3	central back	55	94.81	97.56	12.64	62.25	130.01
		central midfielder	22	100.34	100.17	9.26	85.12	117.22
		central strikers	33	91.21	93.51	10.70	69.62	110.11
		fullback	40	97.65	97.61	10.55	68.16	119.11
		wide midfielder	46	102.87	103.69	9.87	77.42	123.18
		wide strikers	41	96.60	95.92	9.03	77.97	122.75
	MD	central back	100	26.05	26.00	1.90	19.41	32.49
		central midfielder	59	24.98	25.26	1.54	21.37	28.69
		central strikers	94	27.89	28.43	3.64	14.16	33.68
		fullback	103	24.48	24.88	2.71	4.72	29.58
		wide midfielder	117	24.26	23.71	3.08	18.56	34.49
		wide strikers	107	26.67	26.31	2.23	22.47	34.01

	central back	103	24.12	24.08	3.44	17.06	35.08
	central midfielder	43	24.70	24.05	3.69	17.38	36.74
	central strikers	64	25.90	25.78	3.23	17.93	34.14
MD+2	fullback	72	24.07	24.53	3.13	18.06	32.65
	wide midfielder	85	24.18	24.36	3.82	15.86	33.03
	wide strikers	74	25.12	25.40	3.14	12.79	33.49
	central back	88	24.18	24.09	2.43	16.47	29.35
	central midfielder	36	25.32	24.94	2.56	18.90	30.81
	central strikers	52	27.47	26.96	2.79	21.47	34.10
MD+3	fullback	60	24.97	24.75	2.48	21.02	31.90
	wide midfielder	77	24.19	23.97	2.97	19.05	32.15
	wide strikers	64	26.65	26.57	2.65	19.99	31.98
	central back	73	26.81	26.94	2.05	22.80	31.43
	central midfielder	31	26.91	26.78	1.80	23.05	30.37
	central strikers	44	29.57	30.32	2.93	21.13	37.12
MD-1	fullback	55	27.10	27.37	2.31	19.11	33.07
	wide midfielder	64	27.46	27.44	2.75	22.01	33.87
	wide strikers	53	29.43	30.06	3.71	9.20	35.17
	central back	56	27.31	28.07	3.57	17.06	33.44
	central midfielder	25	27.41	27.88	3.25	17.19	32.30
	central strikers	35	28.45	28.41	3.70	17.73	33.99
MD-2	fullback	41	27.87	28.40	3.18	16.63	33.48
	wide midfielder	48	27.95	28.74	3.22	18.16	34.28
	wide strikers	44	29.09	30.00	3.82	20.36	35.32
	central back	55	26.87	27.00	2.95	15.59	31.97
	central midfielder	22	27.11	27.29	2.16	21.87	31.26
	central strikers	33	29.81	30.39	3.10	19.48	34.37
MD-3	fullback	40	27.01	27.24	3.02	16.42	32.96
	wide midfielder	46	25.83	26.11	4.12	5.33	30.61
distance >14.4 Km/h/min	wide strikers	41	29.50	29.40	2.27	24.78	33.99

MD	central back	100	15.49	14.11	17.99	5.03	189.83
	central midfielder	59	18.82	17.69	5.20	9.97	36.28
	central strikers	94	17.03	14.08	21.85	7.86	222.34
	fullback	103	18.69	18.48	4.28	10.43	36.64
	wide midfielder	117	21.40	21.04	4.07	10.06	31.71
	wide strikers	107	19.63	19.71	5.13	8.68	50.31
MD+2	central back	103	22.50	17.90	22.52	2.69	200.71
	central midfielder	43	21.00	20.65	9.65	8.45	45.04
	central strikers	64	20.16	19.04	7.68	8.04	43.88
	fullback	72	20.35	19.23	7.70	4.82	37.49
	wide midfielder	85	20.91	20.18	7.52	4.29	44.63
	wide strikers	74	19.81	18.53	9.82	5.13	82.04
MD+3	central back	88	13.29	12.75	5.10	2.28	28.96
	central midfielder	36	13.46	11.51	5.72	2.76	29.19
	central strikers	52	11.59	11.59	5.06	1.87	22.90
	fullback	60	15.37	15.01	6.21	1.50	30.24
	wide midfielder	77	16.24	16.79	5.87	2.22	28.26
	wide strikers	64	17.61	14.75	23.26	3.97	196.39
MD-1	central back	73	9.10	7.47	6.35	2.20	40.59
	central midfielder	31	8.66	7.59	3.86	2.99	22.13
	central strikers	44	7.30	6.83	3.57	2.66	20.85
	fullback	55	9.97	9.84	3.30	3.55	21.06
	wide midfielder	64	11.80	8.56	22.66	4.55	188.99
	wide strikers	53	9.16	9.07	3.05	3.96	21.05
MD-2	central back	56	9.01	7.75	4.66	3.49	27.93
	central midfielder	25	10.35	10.16	3.88	4.41	17.40
	central strikers	35	8.67	7.40	3.30	4.29	17.06
	fullback	41	9.27	9.09	2.87	4.57	16.40
	wide midfielder	48	11.42	10.85	3.90	4.88	23.29
	wide strikers	44	10.58	10.28	3.45	2.55	17.70

distance >19.8 Km/h/min	MD-3	central back	55	10.88	10.40	3.11	5.46	21.02
		central midfielder	22	13.93	13.07	5.12	6.69	31.85
		central strikers	33	10.92	10.96	2.34	6.05	15.84
		fullback	40	13.69	13.25	4.28	7.02	28.26
		wide midfielder	46	15.73	15.97	3.62	7.45	24.71
		wide strikers	41	13.07	13.52	2.91	6.42	19.04
	MD	central back	100	4.58	4.02	3.69	0.62	32.85
		central midfielder	59	4.64	4.30	1.76	1.40	9.90
		central strikers	94	5.98	5.46	3.00	0.97	22.83
		fullback	103	7.01	6.97	2.02	0.48	12.15
		wide midfielder	117	7.14	7.06	2.37	0.77	20.25
		wide strikers	107	7.95	7.97	2.02	2.70	13.12
	MD+2	central back	103	15.10	14.13	11.27	0.05	64.14
		central midfielder	43	13.28	12.05	9.46	0.64	36.57
		central strikers	64	14.10	14.44	7.77	1.27	33.43
		fullback	72	16.01	14.26	11.24	0.27	42.95
		wide midfielder	85	16.97	17.04	11.45	0.42	45.66
		wide strikers	74	16.14	16.15	10.42	0.52	45.71
	MD+3	central back	88	5.55	3.24	6.70	0.24	41.09
		central midfielder	36	3.43	2.05	3.77	0.69	16.33
		central strikers	52	4.63	2.43	5.18	0.07	21.31
		fullback	60	6.44	4.51	6.10	0.23	27.50
		wide midfielder	77	6.62	4.19	6.73	0.13	29.67
		wide strikers	64	5.78	4.04	5.14	1.09	23.56
	MD-1	central back	73	3.43	2.10	3.79	0.04	21.32
		central midfielder	31	1.56	0.86	1.46	0.06	5.90
		central strikers	44	2.18	1.78	1.88	0.09	7.78
		fullback	55	2.70	2.46	1.50	0.37	7.97
		wide midfielder	64	2.82	2.09	2.84	0.28	19.66
		wide strikers	53	3.06	2.21	2.67	0.30	17.04

distance >25.2 Km/h/min	MD-2	central back	56	3.62	2.06	6.21	0.31	41.48
		central midfielder	25	2.00	1.71	1.03	0.56	4.34
		central strikers	35	2.56	2.01	1.46	0.76	6.71
		fullback	41	3.25	3.03	1.87	0.28	7.67
		wide midfielder	48	3.18	2.94	1.60	0.32	7.93
		wide strikers	44	4.49	3.72	3.94	1.00	25.95
	MD-3	central back	55	6.36	5.52	4.09	1.96	24.59
		central midfielder	22	4.24	4.13	1.52	1.55	7.53
		central strikers	33	5.60	5.75	1.85	1.35	10.91
		fullback	40	6.08	6.07	2.48	0.46	11.09
		wide midfielder	46	6.54	6.49	2.46	0.00	15.53
		wide strikers	41	6.22	6.28	2.25	1.81	13.10
	MD	central back	100	1.07	0.91	0.73	0.00	4.04
		central midfielder	59	0.56	0.50	0.43	0.00	1.84
		central strikers	94	1.81	1.44	1.87	0.00	13.70
		fullback	103	2.32	2.15	1.18	0.00	5.97
		wide midfielder	117	1.78	1.49	1.16	0.00	6.21
		wide strikers	107	2.82	2.50	1.48	0.24	7.73
	MD+2	central back	103	0.40	0.22	0.51	0.00	3.19
		central midfielder	43	0.31	0.08	0.75	0.00	4.86
		central strikers	64	0.42	0.33	0.48	0.00	2.07
		fullback	72	0.65	0.35	0.88	0.00	5.10
		wide midfielder	85	0.63	0.40	0.85	0.00	6.05
		wide strikers	74	0.58	0.37	0.61	0.00	3.41
	MD+3	central back	88	0.37	0.16	0.67	0.00	4.73
		central midfielder	36	0.21	0.07	0.31	0.00	1.52
		central strikers	52	0.37	0.12	0.51	0.00	2.23
		fullback	60	0.69	0.45	0.70	0.00	2.86
		wide midfielder	77	0.49	0.27	0.72	0.00	4.77
		wide strikers	64	0.56	0.43	0.55	0.00	2.59

maxSpeed (km/h)	MD-1	central back	73	0.20	0.12	0.29	0.00	1.62
		central midfielder	31	0.19	0.00	0.30	0.00	0.90
		central strikers	44	0.25	0.04	0.47	0.00	1.85
		fullback	55	0.49	0.26	0.61	0.00	3.27
		wide midfielder	64	0.37	0.11	0.71	0.00	4.41
		wide strikers	53	0.40	0.24	0.51	0.00	2.69
	MD-2	central back	56	0.49	0.35	0.49	0.00	2.49
		central midfielder	25	0.15	0.07	0.20	0.00	0.71
		central strikers	35	0.59	0.52	0.66	0.00	2.89
		fullback	41	0.90	0.80	0.85	0.05	4.36
		wide midfielder	48	0.63	0.53	0.57	0.00	2.86
		wide strikers	44	1.05	0.79	1.33	0.00	7.91
	MD-3	central back	55	2.01	1.36	1.75	0.00	5.94
		central midfielder	22	1.48	0.70	1.69	0.00	5.64
		central strikers	33	2.98	2.40	2.22	0.31	8.23
		fullback	40	2.73	2.25	2.15	0.10	8.38
		wide midfielder	46	2.42	1.78	1.99	0.04	7.98
		wide strikers	41	3.05	1.88	2.76	0.00	9.64
	MD	central back	100	30.65	31.12	2.35	20.79	36.07
		central midfielder	59	28.74	29.21	2.29	22.30	33.69
		central strikers	94	30.75	30.88	2.29	24.47	35.38
		fullback	103	32.38	32.33	2.11	26.05	37.57
		wide midfielder	117	30.49	30.54	1.95	24.80	34.72
		wide strikers	107	31.80	32.12	2.20	25.37	36.00
	MD+2	central back	103	27.62	27.42	2.08	22.74	32.73
		central midfielder	43	26.80	26.45	2.11	23.24	32.89
		central strikers	64	28.00	27.67	2.14	23.26	32.45
		fullback	72	28.56	28.21	2.51	23.17	34.31
		wide midfielder	85	28.54	28.84	2.50	22.78	35.02
		wide strikers	74	28.44	28.57	2.17	20.32	33.44

MD+3	central back	88	27.63	27.22	2.67	22.22	35.09
	central midfielder	36	27.08	26.55	2.32	22.78	31.72
	central strikers	52	27.13	27.04	2.40	22.08	31.40
	fullback	60	28.89	29.25	2.43	24.23	34.32
	wide midfielder	77	27.84	28.00	2.10	23.69	32.65
	wide strikers	64	28.91	29.01	2.44	21.77	35.47
MD-1	central back	73	26.88	26.65	2.72	21.58	32.11
	central midfielder	31	26.00	25.08	3.03	21.62	32.69
	central strikers	44	26.53	26.24	2.82	21.91	33.73
	fullback	55	28.33	28.26	2.75	22.03	33.59
	wide midfielder	64	27.11	27.15	2.85	21.31	32.92
	wide strikers	53	28.03	27.51	2.68	22.74	33.14
MD-2	central back	56	28.45	28.78	2.14	20.64	32.07
	central midfielder	25	27.35	27.15	2.58	23.85	33.91
	central strikers	35	29.14	29.38	2.12	24.84	33.05
	fullback	41	30.17	30.18	2.27	25.91	34.71
	wide midfielder	48	29.27	29.37	1.89	24.54	33.77
	wide strikers	44	29.39	29.81	2.47	22.09	33.14
MD-3	central back	55	30.36	30.37	2.22	22.81	34.13
	central midfielder	22	29.13	29.31	2.17	25.15	32.70
	central strikers	33	31.09	31.03	1.60	28.16	33.88
	fullback	40	31.29	31.98	2.80	22.47	34.88
	wide midfielder	46	30.62	30.96	1.90	24.73	33.94
	wide strikers	41	30.67	31.10	2.95	22.80	35.29

Legend: MD: match day; RPE: rating of perceived exertion; AU: arbitrary units

Table 3.10 summarizes the performance of the LGBM model in predicting players' MD type profiles. The model achieved a mean accuracy score of 84%, demonstrating a strong ability to predict

different MD type. The AUC was 0.97, indicating excellent performance in predicting MD type. The F1 score, a weighted average of precision and recall, further supports this conclusion. Both precision and recall scores were 84%, showing that the model correctly predicted over 84% of positive cases and accurately identified 84% of actual positive classes. The Kappa score was 0.80, indicating good reliability, while Matthew's Correlation Coefficient (MCC) was also 0.80, reflecting strong predictive power. Overall, these findings suggest that the LGBM model performed well in predicting MD type based on internal and EL intensity indicators.

Table 3.10 Performance evaluation of the LGBM model for predicting player profiles across all MD types

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Mean	0.843	0.977	0.843	0.845	0.841	0.807	0.808
Std	0.043	0.014	0.043	0.042	0.044	0.053	0.053

Figure 3.9 illustrates the training and cross-validation scores of the model on the holdout dataset. The training score was 1.00, while the cross-validation score was 0.84. The drop-in scores after cross-validation can be attributed to the data-splitting process for training and testing. The initial training score might have included noise and errors, leading to an inflated accuracy rate (440). However, during cross-validation, the model was adjusted and refined, resulting in a prediction accuracy score of 84%. This outcome highlights the model's efficiency and optimal fit, demonstrating its robust predictive capability while mitigating any overfitting that may have occurred during the initial training phase.

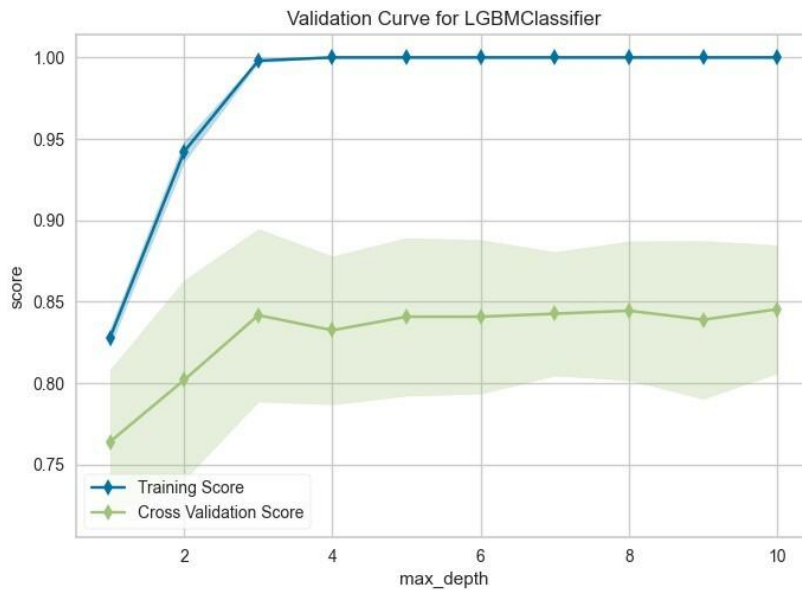


Figure 3.9 Performance of the LGBM model on validation data.

Figure 3.10 highlights the results of the LGBM model analysis for classifying MD types profiles during cross-validation. Cross-validation is crucial for validating the model's effectiveness on untrained data. In this stage, 463 held-out observations were used to test the LGBM model's accuracy. The F1, precision, and recall scores remained reasonably good, accurately predicting MD types profiles for MD-3 (47 instances), MD-2 (57 instances), MD-1 (61 instances), MD+3 (83 instances), MD+2 (92 instances) and Official MD (123 instances). These scores demonstrate that the model maintained good performance and reliability, even when tested on reserve data, reinforcing its predictive accuracy and generalizability.



Figure 3.10 Classification Report for Validation Data in the Developed Model (0 = MD, 1 = MD+2, 2 = MD+3, 3 = MD-1, 4 = MD-2, 5 = MD-3).

Figure 3.11 provides a detailed breakdown of the LightGBM confusion matrix model's performance in classifying MD type based on external and IL metrics. The model demonstrates a satisfactory level of accuracy, particularly in predicting classes MD+2, MD+3, and MD-2. In MD+2, the model correctly classifies 78 out of 81 instances, with only 3 misclassifications. In MD+3, the model correctly classifies 67 out of 74 instances, with 7 misclassifications while in MD-2, the model correctly classifies 47 out of 52 instances, with 5 misclassifications. Moreover, the model misclassifies 7 MD instances as MD-1, while correctly classifying 116 instances while the model misclassifies 4 MD-1 instances as MD-3, while correctly classifying 78 instances. Overall, the confusion matrix demonstrates the model's reasonable performance in the classification task, accurately identifying all the MD types with noteworthy accuracy. This level of accuracy accentuates the effectiveness of the LGBM model in classifying MD types based on the internal and EL indicators in soccer.

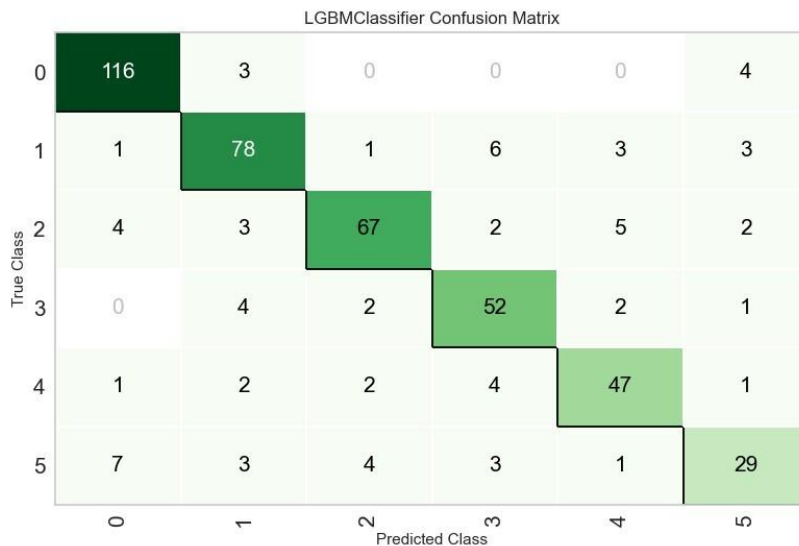


Figure 3.11 Confusion Matrix for MD types Prediction Using the LGBM Model on Validation Data (0 = MD, 1 = MD+2, 2 = MD+3, 3 = MD-1, 4 = MD-2, 5 = MD-3).

Table 3.11 showcases the LGBM model's performance on unseen data, using 30% (661 observations) of the original dataset that were not included in the training and validation phases. The model achieved good 85% accuracy, correctly classifying 578 out of 661 observations, with only 83 misclassifications. This good level of accuracy and consistency accentuates the model's robust ability to classify MD types profiles effectively, demonstrating its practical applicability. Nonetheless, it is worth noting that Table 3.11 displays the first 35 observations, while the complete list is available in Appendix 1. These results confirm the LGBM model's reliability in predicting players' performances across different MD types based on IL and EL intensity indicators.

Table 3.11 Independent Testing for Model Performance Evaluation on Fresh Data

Observations	Actual-MD types	Predicted- MD types	Prediction score
1	MD+2	MD+2	1.00
2	MD+2	MD+2	1.00
3	MD+2	MD+2	1.00
4	MD+2	MD+2	1.00
5	MD+2	MD+2	1.00
6	MD+2	MD+2	1.00
7	MD+3	MD-2	0.98

8	MD+3	MD+3	0.68
9	MD+3	MD+3	0.74
10	MD+3	MD+3	0.98
11	MD+3	MD+3	0.99
12	MD+3	MD+3	0.98
13	MD+3	MD+3	1.00
14	MD+3	MD+3	0.98
15	MD+3	MD+3	0.92
16	MD-2	MD-2	0.99
17	MD-2	MD-2	0.79
18	MD-2	MD-2	0.97
19	MD-1	MD-1	0.97
20	MD-1	MD-1	1.00
21	MD-1	MD-1	1.00
22	MD	MD	1.00
23	MD+2	MD+2	1.00
24	MD+2	MD+2	1.00
25	MD+2	MD+2	1.00
26	MD+2	MD+2	1.00
27	MD	MD	1.00
28	MD	MD	1.00
29	MD	MD	0.94
30	MD	MD	0.99
31	MD	MD	1.00
32	MD	MD	1.00
33	MD	MD	1.00
34	MD	MD	1.00
35	MD	MD	1.00

Feature Importance Investigation

Figure 3.12 illustrates the evaluation of feature importance, highlighting the external and IL indicators that significantly impact model performance. The analysis reveals that session duration training total distance per minute, distance >14.4 km/h per minute, distance >19.8 km/h per minute, acceleration per minute, deceleration per minute as well as distance 0-7 km/h per minute are crucial contributors to the model's accuracy. These parameters are essential for determining MD types considering both training and matches in soccer. Therefore, coaches and trainers should prioritize these metrics to optimize physical performance.

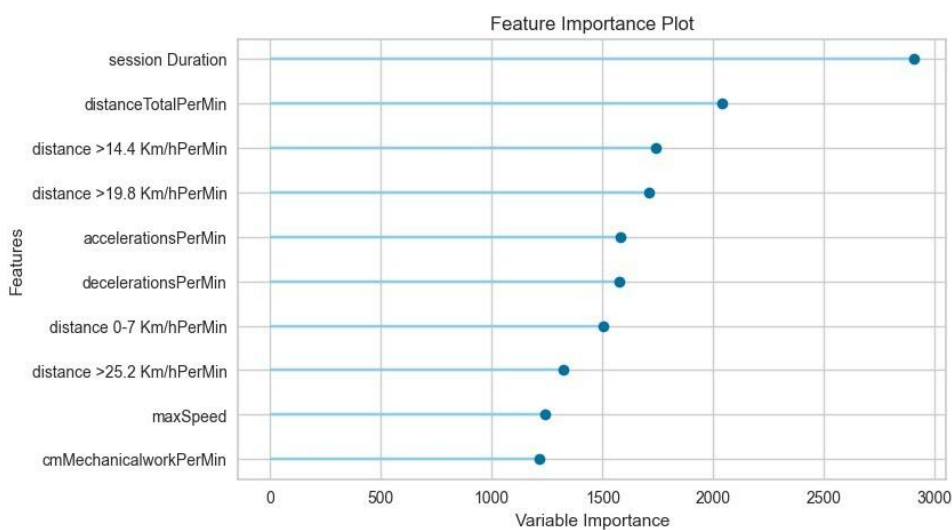
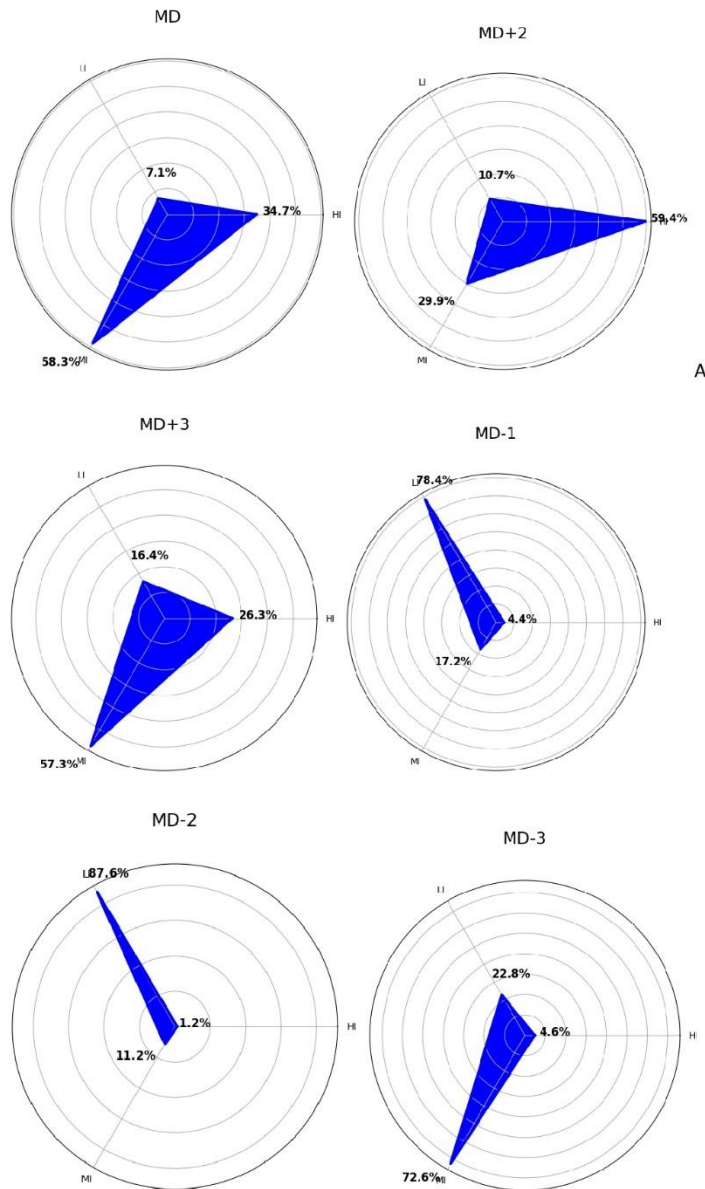


Figure 3.12 Contribution of parameters to LGBM Model Performance.

Figure 3.13 illustrates the intensity profiles across different MD types. Based on the clustering analysis carried out and described earlier, three clusters were discovered by the k-means clustering algorithm i.e. high, medium, and low intensity. As depicted in the Figure 5, Medium-intensity profiles are predominantly associated with official MD (58.3%), MD+2 is highly attributed with high intensity (59.4%), MD+3 is predominantly associated with medium intensity (53.7%), and MD-1 and MD-2 are highly associated with low intensities (78.4% and 87.6%) respectively. Conversely, MD-3 is mainly linked with medium intensity (72.2%).



A

Figure 3.13 Intensity profile across different match day (MD) types.

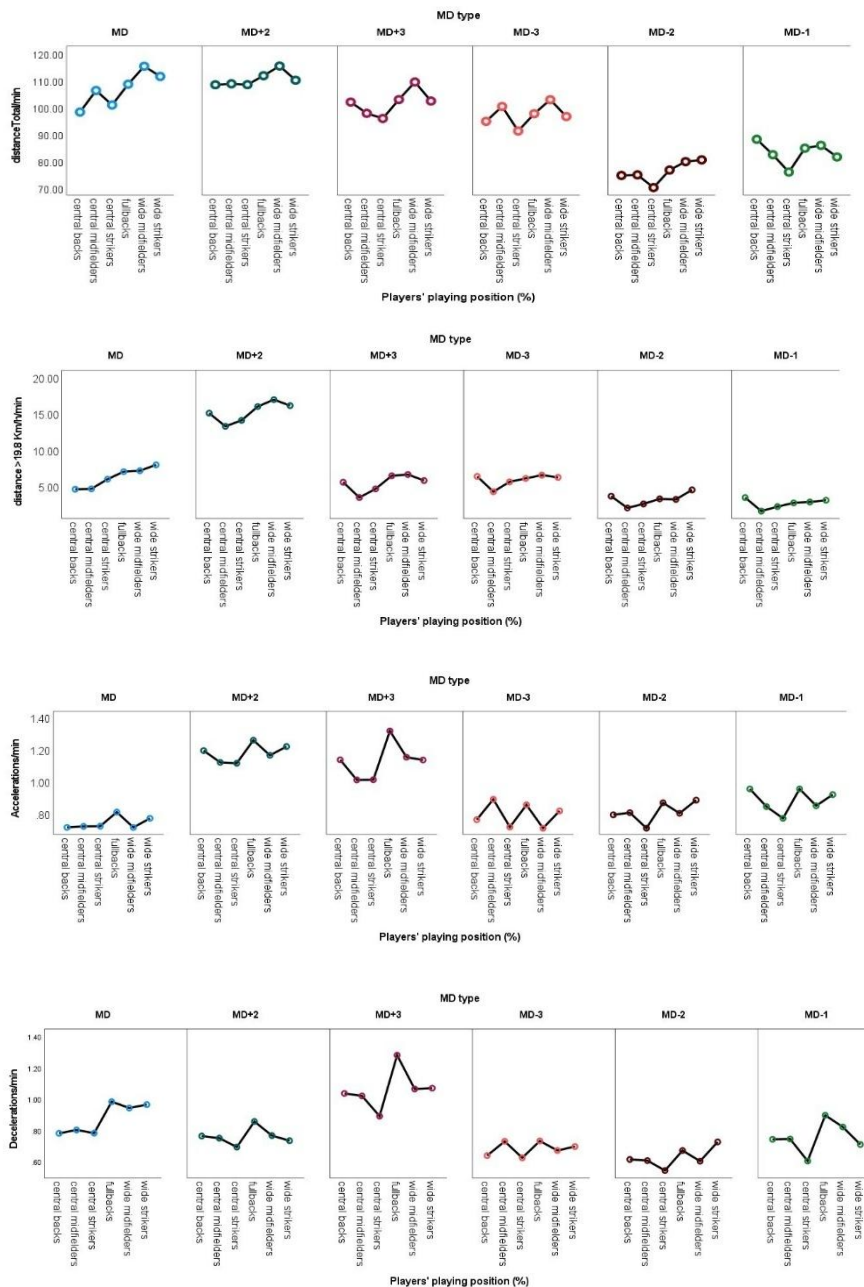


Figure 3.14 Comparative MD types profile across all playing positions (a) distanceTotal/min; (c) distance > 19.8 km/h/min; (d) Accelerations/min; (e) decelerations/min

Analysis of MD types Across Different Playing Positions

Figures 3.14 (a-f) showcases a series of profile plots illustrating the distribution of key internal and external parameters for various playing positions across six MD types (MD, MD+2, MD+3, MD-

1, MD-2, MD-3). The plots are organized in a grid, with each row representing a different playing position (e.g., CB, central MDF) and each column corresponding to a different MD type. Since the session duration is the same for all players, we did not consider the plots of the variations of the session duration across playing positions.

The two-way mixed-design ANOVA revealed a significant interaction between playing position and MD types on distance Total/min ($F(25, 2168) = 2.764, p < .001$). The interaction plot (Figure 3.14a) illustrates that the patterns of change in distance Total/min across MD types varied across playing positions. WM consistently maintain a relatively high distance Total/min across most MD types, visually comparable to or exceeding other positions, particularly on MD, MD+2, MD+3, and MD-1. The post-hoc tests reveal statistically significant differences between WM and other positions. The WM are significantly different from CB, MDF, and WS, on MD-1, MD-2 as well as MD-3, while significant differences exist across all positions where the WM demonstrated higher performance on all MDs ($p < .001$).

The two-way mixed-design ANOVA revealed no significant interaction between playing position and MD types on the distance travelled above 14.4 km/h ($F(25, 2168) = 0.952, p = 0.531$). This indicates that the effect of MD types on the distance travelled above this speed threshold is consistent across all playing positions as illustrated in the interaction plot in Figure 3.14b (supplementary). In other words, the way distance travelled above 14.4 km/h changes throughout the MD types is similar for all player roles. Similarly, the findings revealed no significant interaction between playing position and MD types on the distance travelled above 19.8 km/h ($F(25, 2168) = 0.843, p = 0.688$). This indicates that the effect of MD types on the distance travelled above this higher speed threshold is consistent across all playing positions as depicted in Figure 7c. The two-way mixed-design ANOVA also revealed no significant interaction between playing position and MD types on the number of accelerations per minute ($F(25, 2168) = 1.28, p = 0.162$) as indicated in Figure 3.14d.

The analysis further revealed a significant interaction between playing position and MD types on decelerations per minute ($F(25, 2168) = 1.58, p = 0.033$). The interaction plot (Figure 3.14e) illustrates that the patterns of change in decelerations per minute across MD types varied across playing positions. FB demonstrated a distinct peak in decelerations per minute on MD-2. The post-hoc tests reveal statistically significant differences between FB and other positions on MD-2. Specifically, FB are significantly different from CB, MDF, CS, WM, and WS on MD-2 ($p < .001$). Additionally, CB showed significantly lower decelerations per minute than FB on MD+3 ($p < .001$).

Moreover, the results indicated a significant interaction between playing position and MD types on distance travelled at speeds 0-7Km/h/min ($F(25, 2168) = 2.41, p < .001$). The interaction plot (Figure 3.14f supplementary) illustrates that the patterns of change in distance travelled at lower speeds across

MD types varied across playing positions. CS consistently performed a higher amount of distance at lower speeds across MD types compared to other positions. The post-hoc tests reveal statistically significant differences between CS and other positions. Specifically, CS are significantly different from CB, central MDF, FB, wide MDF, and WS across all MD types ($p < .001$). Additionally, on MD-1, MD-2, and MD-3, MDF performed a significantly lower amount of distance at lower speeds compared to other positions ($p < .001$). On MD+3, WS performed a significantly higher amount of distance at lower speeds compared to other positions except for CS ($p < .001$).

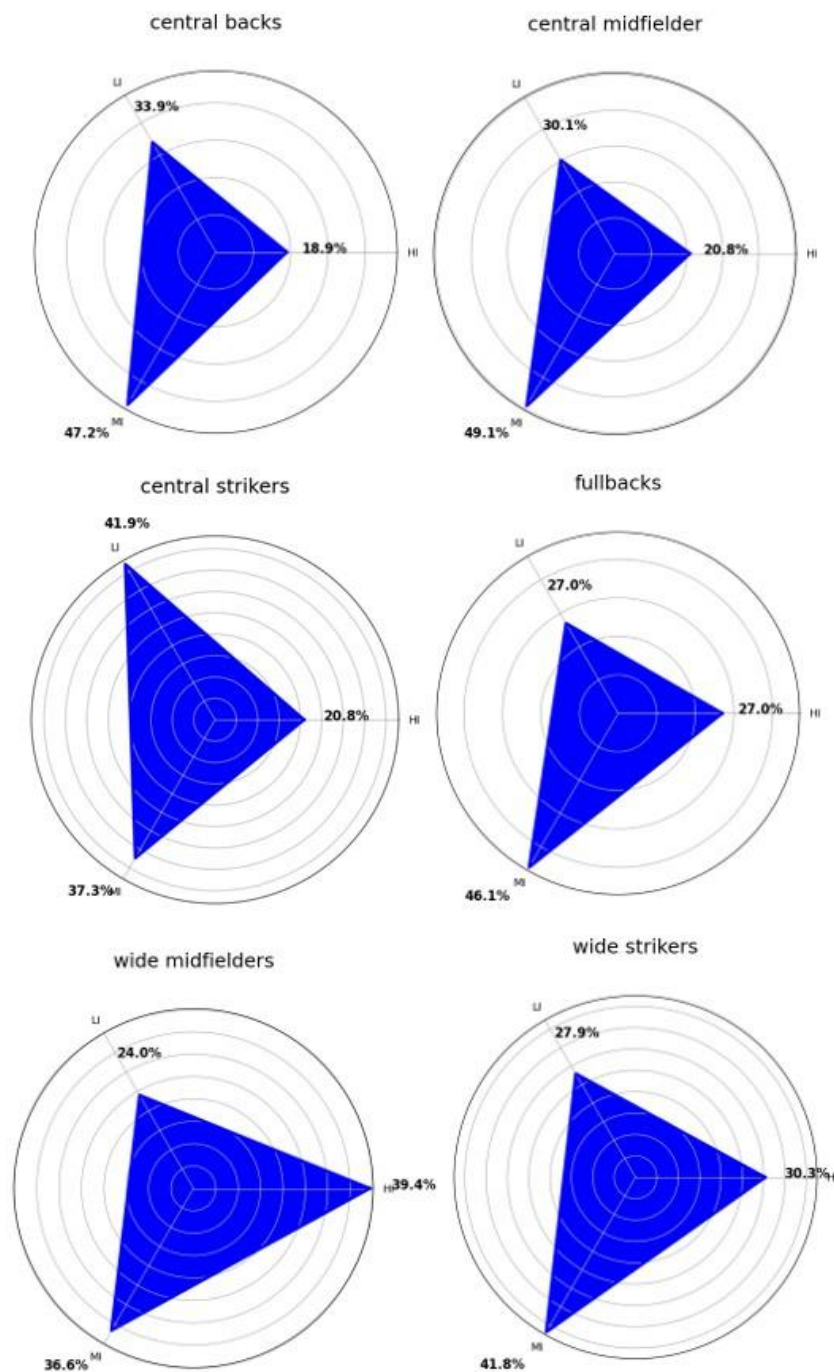


Figure 3.15 Intensity profile across playing positions.

Figure 3.15 illustrates the intensity profiles across different playing positions. Medium-intensity profiles are predominantly associated with CB (47.2%), central MDF (49.1%), full-backs (46.1%), and WS (41.8%). Low-intensity profiles are mainly linked to CS (41.9%), while wide MDF tend to exhibit high-intensity profiles, covering 39.4%. Additionally, Figure 3.16 presents a comparative cumulative analysis of intensity profiles across various playing position, considering all examined internal and external parameters.

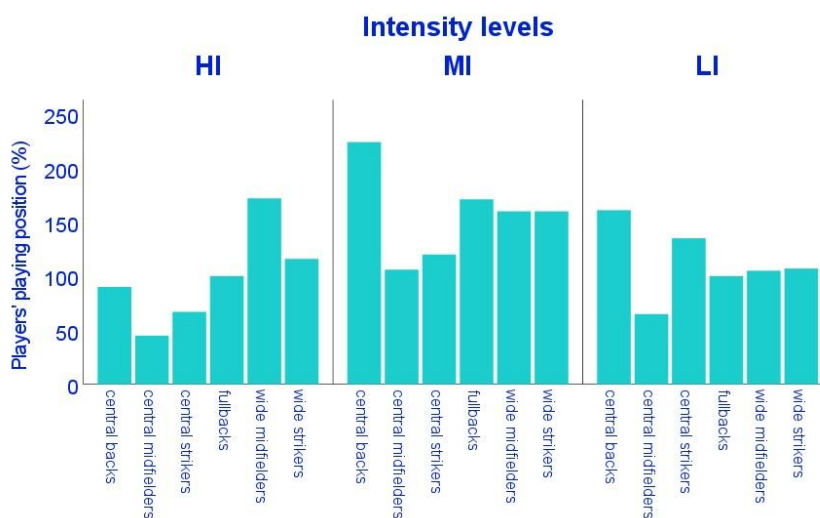


Figure 3.16 Comparative Intensity profile across all playing positions

Discussion

A ML approach was employed in this study aiming to provide insight on intensity within a standard microcycle considering playing position. In detail, through k-means clustering analysis we have identified three intensity levels: low medium, and high. The AUC was 0.99, indicating excellent performance in predicting intensity levels. These findings highlight the effectiveness of the k-means analysis in categorizing players' intensity levels based on all measured internal and external parameters. To the authors knowledge, only a previous study (262) has clustered 5 match intensity profile considering EL indicators, employing a ML approach (A non-supervised machine learning model [k-means] based on the components derived from Principal Component Analysis [PCA]).

In soccer, PCA has been used to analyze TL data and identify key parameters representing player demands. Oliva-Lozano et al. (441) applied PCA to EL metrics from professional players,

revealing that a few variables explained most of the TL variance. While effective for dimensionality reduction, PCA's linear approach limits its ability to capture the complex, multifactorial interactions inherent in team sports like soccer. These interactions involve dynamic relationships between physiological responses, tactical roles, environmental factors, and player-specific characteristics, where advanced ML techniques offer deeper insights into performance and injury risks.

Moreover, the evaluation of feature importance, highlighting the external and IL parameters, showed a significantly impact on the model performance. In particular, the analysis reveals that training total distance per minute, distance >19.8 km/h per minute, distance >14.4 km/h per minute, distance 0-7 km/h per minute, and the RPE are crucial contributors to the model's accuracy. These parameters are essential for determining players' intensity levels during all training sessions and matches in soccer for a standard microcycle.

In our analysis of MD types within a standard microcycle, we observed variability in their intensity profiles. Specifically, the LGBM model in predicting players' MD type profiles, achieved a mean accuracy score of 84%, as well as the AUC was 0.97, demonstrating a strong ability to predict different MD types through intensity external and IL indicators. Moreover, the LightGBM confusion matrix model's performance in classifying MD types demonstrates a satisfactory level of accuracy, particularly in predicting classes MD+2, MD+3, and MD-2 highlighting that each MD type is strongly characterized by specific physical target. Indeed, MD+2 is characterized by metabolic target, including HIT drills (with and without ball) eliciting the highest values of distance >19.8 Km/h/min as well as distanceTotal/min compared to others MD type. While MD+3 shows the highest values of mechanicalwork/min coherently with the session target (i.e., neuromuscular/specific strength) where specific drills such as small sided games are performed. The lowest values of distanceTotal/min and the highest values in distance 0-7 Km/h/min (i.e., walking) characterized MD-2 in line with the standard microcycle programming strategies where tapering phase results in MD-2 and MD-1. These results corroborate with a systematic review, authored by Silva et al., who investigates the dynamics of training load across a soccer microcycle. The review emphasizes the critical role of periodization—structuring training within a week to balance intensity and recovery. Indeed, soccer microcycles typically follow a pattern of higher-intensity sessions midweek (e.g., MD-3) and lower-intensity sessions closer to (MD-1). This structured approach supports the dual goals of physiological capacity development and injury risk mitigation. The review highlights that MD has the highest physical demands, while midweek sessions often match or exceed this intensity to develop attributes like speed, endurance, and strength, consistent with our findings. Conversely, sessions immediately following or preceding matches (MD+1 and MD-1) are reserved for recovery for starters (players who participated for at least 60 minutes) and integrative training for no-starters (player who were

either not used or played less than 30 minutes) (271) while MD-1 represent a tapering day, ensuring players are adequately prepared for competition (7). In the same way, Pillitteri et al., (87) have applied a ML approach to computed two score (derived from internal and EL indicators). Authors found a statistical difference among microcycle days and playing position.

Concerning, the evaluation of feature importance, session duration, total distance per minute, distance >14.4 km/h per minute, distance >19.8 km/h per minute, acceleration per minute, deceleration per minute as well as distance 0-7 km/h per minute are crucial contributors to the model's accuracy. These parameters are essential for determining MD types considering both training and matches in soccer. Based on the k-means clustering algorithm (i.e. high, medium and low intensity), medium-intensity profiles are predominantly associated with official MD (58.3%), MD+2 is highly attributed with high intensity (59.4%), MD+3 is predominantly associated with medium intensity (53.7%), and MD-1 and MD-2 are highly associated with low intensities (78.4% and 87.6%) respectively. Conversely, MD-3 is mainly linked with medium intensity (72.2%). This type of training session is focused on tactical objectives, with drills designed in large spaces that emphasize high-speed running and sprinting, as demonstrated by our results. However, some studies have reported higher training loads on MD-3, suggesting variability in periodization strategies among teams (416). Each MD type has specific objectives, with certain exercises causing higher intensity indicators, highlighting the specificity of each parameter. This aligns with Pillitteri et al. (230), who stress that combining multiple external intensity indicators is essential for a holistic assessment of soccer physical performance. Concerning the intensity profile across different playing position, we identified variations in intensity among playing positions throughout a standard microcycle. In detail, CB (47.2%), central MDF (49.1%), full-backs (46.1%), and WS (41.8%) were classified as medium-intensity profiles. Low-intensity profiles are mainly linked to CS (41.9%), while wide MDF tend to exhibit high-intensity profiles, covering 39.4%. These results align with Sarmiento et al. (442), who found that central and external MDF, along with defenders, cover more total and high-speed distances than forwards or central defenders, with external MDF leading in sprint distances. Similarly, our study shows that full-backs, wide MDF, and WS have higher values for distances >19.8 km/h/min and >25.2 km/h/min compared to other positions.

We reported the distribution of key internal and external parameters for each playing positions across six MD types. For example, CB and central MDF generally show lower values compared to wide players and forwards while CB and central MDF exhibit lower distances per minute on MD-3 compared to other days. Regarding the high-intensity distance (>14.4 km/h/min), attacking positions like wide forwards and wide MDF cover more distance per minute than defensive positions like CB.

Studies indicate that players in wide positions cover greater high-intensity distances and sprinting distances, as the available space allows them to reach higher speed (418). A study using a machine learning approach identified specific intensity profiles based on training drill objectives, considering both neuromuscular and metabolic components (262). Through a data-driven method, the authors evaluated soccer task intensity to assess player performance efficiently. The model moderately distinguished playing positions, with wide MDF often being confused with external strikers due to similar tactical demands. Literature shows that physical performance, assessed through EL indicators vary across playing position (87, 262, 417, 442). The study of TL is inherently complex, and conclusions must be contextualized to the specific sample examined. Numerous factors, including training status, methodology, level of competition, and type of training, can influence both external and IL (considering both absolute or relative [intensity] indicators).

This study presents some limitations. Data has been collected in male professional soccer players including both training and match. Accordingly, care should be taken when generalizing these findings as physical performance is strictly related to the specificity of the context. Various external (environmental) and internal factors (psychological aspects, stress, sleep, fatigue) can influence physical performance during matches and training. For instance, coaches' tactical requirements (e.g., 1-4-3-3 vs. 1-3-5-2 formations) lead to different EL responses. Future studies should expand the sample size, incorporating different competition levels, tactical demands, and other sports to enhance the robustness of ML analysis. Moreover, other ML models could be explored for their predictive accuracies in ascertaining workload demands for different MD types, different microcycle (with different length and number of match) considering playing position.

Practical Application

This study highlights the value of integrating machine learning into sports performance analysis, providing coaches with predictive insights to enhance performance management and reduce injury risks. The analysis offers benchmark references for training and competition in professional men's soccer, helping plan microcycle sessions based on intensity targets for different MD types and playing positions.

The model accurately distinguishes intensity levels between MD types, identifying higher HSR and sprint distances in MD+2 and MD-3 compared to lower-intensity recovery sessions like MD-1. Using k-means clustering, it effectively groups players by intensity profiles: wide MDF show

high-intensity profiles, CB and MDF exhibit medium intensity, and CS are linked to lower intensity. These findings reflect the specific physical demands of each playing position.

Conclusion

This study demonstrates the effectiveness of advanced machine learning, particularly k-means analysis, in categorizing players' intensity levels based on internal and EL parameters. The ML model achieved 84% accuracy with an AUC of 0.97 in predicting MD types profiles, with key contributors including total distance per minute, distances covered at >19.8 km/h, >14.4 km/h, 0–7 km/h per minute, and RPE. Significant variations in intensity and training load were identified across MD types as well as between playing positions, reflecting distinct physical and tactical demands. Wide players recorded higher sprinting distances per minute, while central MDF displayed greater overall intensity across key performance indicators. These findings highlight the importance of tailoring training programs to the specific demands of each position within a standard microcycle.

3.5 Association between internal load responses and recovery ability in U19 professional soccer players: A machine learning approach

Pillitteri G, Rossi A, Simonelli C, Leale I, Giustino V, Battaglia G. (2023). Association between internal load responses and recovery ability in U19 professional soccer players: A machine learning approach. *Heliyon*. 2023 Apr 13;9(4):e15454.

1. Introduction

The objective of soccer training is enhancing the players performance while minimizing the possible negative effects induced by fatigue such as injuries (2, 3, 407, 443-445). It is well known that soccer players are subjected to a given load during both training and competitions that induces a certain degree of neuromuscular, metabolic and mental fatigue. Indeed, the improper management of (TL) could be considered as one of the main risk factors in non-contact injuries (155, 446, 447). TL has been defined as “a higher-order construct reflecting the amount of physical training that is actually done and experienced by the athletes” (4, 446, 448, 449). Training loads is described by its two components known as internal (IL), and external (EL) loads (158, 450, 451). The EL induces internal responses that reflect psychological, physiological, biochemical, metabolic, and biomechanical stress stimuli (57, 158, 452, 453). Meanwhile, the acute dose–response paradigm indicates that specific internal responses such as heart rate (HR) or rating of perceived exertion (RPE), are induced by external training factors (57, 285, 454) (e.g., high speed distance, sprinting distance, metabolic power and accelerations/decelerations). Hence, monitoring EL and IL is essential for the management of soccer players during both training and competition to maximize athletic performance and potentially minimize injurie’s risk (9, 283, 285). Actually, when high-load training is prolonged with an inadequate balance between training volume, intensity and recovery can lead to poor adaptation (237, 455, 456) inducing a condition of overreaching (455, 457). Kenttä and Hassmén (1998) indicated that training recovery is a critical component for adaptation and performance, and it permits to avoid the potential maladaptive physical and psychological effects of fatigue (237, 449). Indeed, Nédélec, et al., (2015) reported that high TL reduces wellness and is related to the perceived sleep, stress, fatigue, and muscle soreness in professional soccer players (455, 458, 459). In this way, literature suggests of evaluating muscle soreness and fatigue during and after each exercise session to understand the recovery state from workload (2, 26, 27, 407, 460). Several researches related to markers of fatigue and recovery have been conducted in sports science and exercise physiology area (461-465). Those included biochemical (407, 466), hormonal (407, 466), immunological (461, 467, 468), psychological questionnaires (456, 462, 469, 470), and the assessment of neurological status,

such as autonomic nervous system balance (443, 471). However, although a good number of scientifically reliable indicators exist, there is currently no single conclusive marker of fatigue (26, 407, 472). Therefore, the use of psychological questionnaires to monitor fatigue and recovery status could also be useful as they are inexpensive and easy to apply compared to more complex laboratory assessments (8, 26). Validated self-report questionnaires that are frequently used by authors include the Profile of Mood States (POMS), Total Quality Recovery (TQR), Daily Analysis of Life Demands for Athletes (DALDA), the Recovery Stress Questionnaire for Athletes (REST-Q), the Acute Recovery and Stress Scale (ARSS), and the Rating of Fatigue Scale (ROF (473)). Interestingly, the use of personalized self-assessment questionnaires has increased compared to the questionnaires published in the literature (474, 475).

Since recovery is a critical period between successive training sessions or competitions potentially necessary to improve subsequent performance (i.e., supercompensation, so-called psychophysiological process for reducing fatigue and regaining vigor (456)), the main objective of the TQR scale is to prevent the onset of fatigue and try to find a balance between training and recovery (476). In this context, Selmi et al. 2018 (477) highlighted that TQR and Hooper Index (HI) (i.e., sleep quality, overall stress, fatigue, and DOMS) are useful to monitor the effects of TL and sensitive to stress and recovery (462) assessment. For example, HI and TQR scores are significant predictors of performance in soccer players (461, 478) with increasing HI and TQR scores significantly associated with high TL (461, 464, 479). Interestingly, a review carried out by Selmi et al. (2022), reported that HI and TQR recorded before each training session or match were influenced by the variability of TL and influenced the physical and technical performances (480). However, some authors found no significant association between the TQR, wellbeing status and the RPE in soccer (443, 446, 477, 480). These controversial results could be due to the typology of analysis conducted. Indeed, their analytical approach is mono-dimensional, i.e., they use just one variable at time without fully manipulating the complex patterns (i.e., TL) inherent the available data. Differently, to the best of our knowledge, only few studies, including the one carried out by Rossi et al., 2019 (15), applied advanced and complex analysis such as machine learning approaches to investigate the relationship between TL and wellness and recovery. In this perspective, the authors found that it is possible to accurately estimate the wellness status of the players based on their workload history (15). These approaches could help to better understand the implications of TL on players' wellness and recovery status, allowing the development of mathematical models able to give accurate prediction and consequently possible useful insights about injury risks (309, 310, 481-483) and internal TL (484).

Considering that previous studies highlight the strong mono-dimensional relationship between TL and individuals' wellbeing, and the conflicting result of this statement, the aim of this study is to better understand the complex relationship between internal training load (using RPE methods) and recovery state and availability (i.e., subjective players' readiness status). With the tool, practitioners could easily simulate players' response to planned training in order to maximize the training effect and possibly reduce the injury risk.

2. Methods

2.1.Experimental Approach to the Problem

In this cross-sectional study, players from a professional Italian soccer club were monitored using RPE scale to assess internal load and TreS scale to detect information about recovery and training/match availability during the entire season (2021-2022).

2.2.Subjects

Twenty-two-professional soccer players (age: $18,5 \pm 0,4$ years, height: 177 ± 6 cm, weight: $67 \pm 6,7$ Kg) competing in the U19 Italian Championship were analysed. The following inclusion criteria were considered: 1) professional male soccer players; 2) no injury in the previous six months. Based on the exclusion criteria, only the goalkeepers were not eligible for the study. The duration of the training sessions was approximately 110 min and mainly included technical-tactical team tasks along with some general physical exercise without ball (e.g., high intensity interval training, HIIT (8, 9)). Strength and conditioning exercises were performed twice a week (i.e., one session in the gym and one session on the pitch). All participants signed an informed consent before taking part in the data collection. The study, which complies with the principles of the Declaration of Helsinki, was approved by the Bioethics Committee of the University of Palermo (n. 68/2021).

2.3.Procedures

Participants were monitored during training and official matches performed on a third-generation artificial pitch or natural grass. All players performed a typical 25-minute pre-match warm-up before OM and 30' before training (15' specific activation in the gym and 15' on field warm-up). Data was collected through RPE scale. Training Load (TL) was calculated multiplying training durations and RPE value. during the entire 2021-2022 season. To estimate the players' state of recovery, the TreS scale was used.

Soccer players were categorized into six groups according to their role as follows: central back (CB), external strikers (ES), fullback (FB), midfielder (MD), wide midfielder (WM) and Strikers (S).

2.4.Measures

2.4.1. Internal Load assessment

TL for each participant was calculated according to the session-RPE method of Foster et al. (2001). 30 min after each session, the duration (minutes) and each RPE training session were recorded for players using smartphone applications (i.e., WhatsApp through a broadcast list). TL from each session for each player was calculated from the product of the session duration and the player's RPE (Foster et al., 2001). The training session duration included warm up, cool down and rest between tasks.

2.4.2. Recovery assessment

To estimate the players' state of recovery, the TreS scale that includes both Global Quality Recovery (GQR) and Training Intensity Availability (TIA) was used.

Global Quality Recovery (GQR) ranging from "I have not recovered at all", 0 points, to "full recovery", 10 points) presented to the athletes before the daily training session through WhatsApp using the question: "What is your physical recovery condition now?". Training Intensity Availability (TIA) ranging from "Complete rest", 0 points, to "Ready for competition", 10 points. Athletes answer the following question: "What is your availability to train or compete?"

2.5. Data Analysis

The autocorrelation analysis was conducted in order to detect similarity between observations in the variables (i.e., TL, Recovery and Availability) time series as a function of the time lag between them. Autocorrelation is the correlation of a signal with a delayed copy of itself as a function of delay. The analysis of autocorrelation is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal obscured by noise or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. In statistics, the autocorrelation of a real or complex random process is the Pearson correlation (r) between values of the process at different times, as a function of the two times or of the time lag.

A cross-correlation analysis was conducted in order to detect correlations between two time series. Cross-correlation is a measure of similarity of two series of data as a function of the displacement of one relative to the other. The term cross-correlations refers to the correlations between the entries' time series.

Mediational analysis was conducted in order to detect the mediators that affect the relationship between TL and Recovery of the next day. In order to take in consideration, the assumption of related pairs, a repeated measures mediational analysis was performed. In particular, Marginal Regression Model using Generalized Estimating Equations based on Autoregressive covariance structure was used to meet both time series and repeated measures assumptions.

All the analyses were performed by using python 3.8 programming language.

3. Results

3610 observations were recorded for this study. In total, 191 training sessions (112.81 +/- 55.96 trainings per player) were analysed. Figure 1 shows the timeseries of TL, Recovery and Availability. The descriptive statistics for all the features was provided in Table 3.12.

Table 3.12 Descriptive statistics.

	TL	Recovery	Availability
mean	376.41	7.35	7.36
std	203.95	1.01	1.00
min	20	4	1
25%	240	7	7
50%	360	7	7
75%	480	8	8
max	1620	10	10

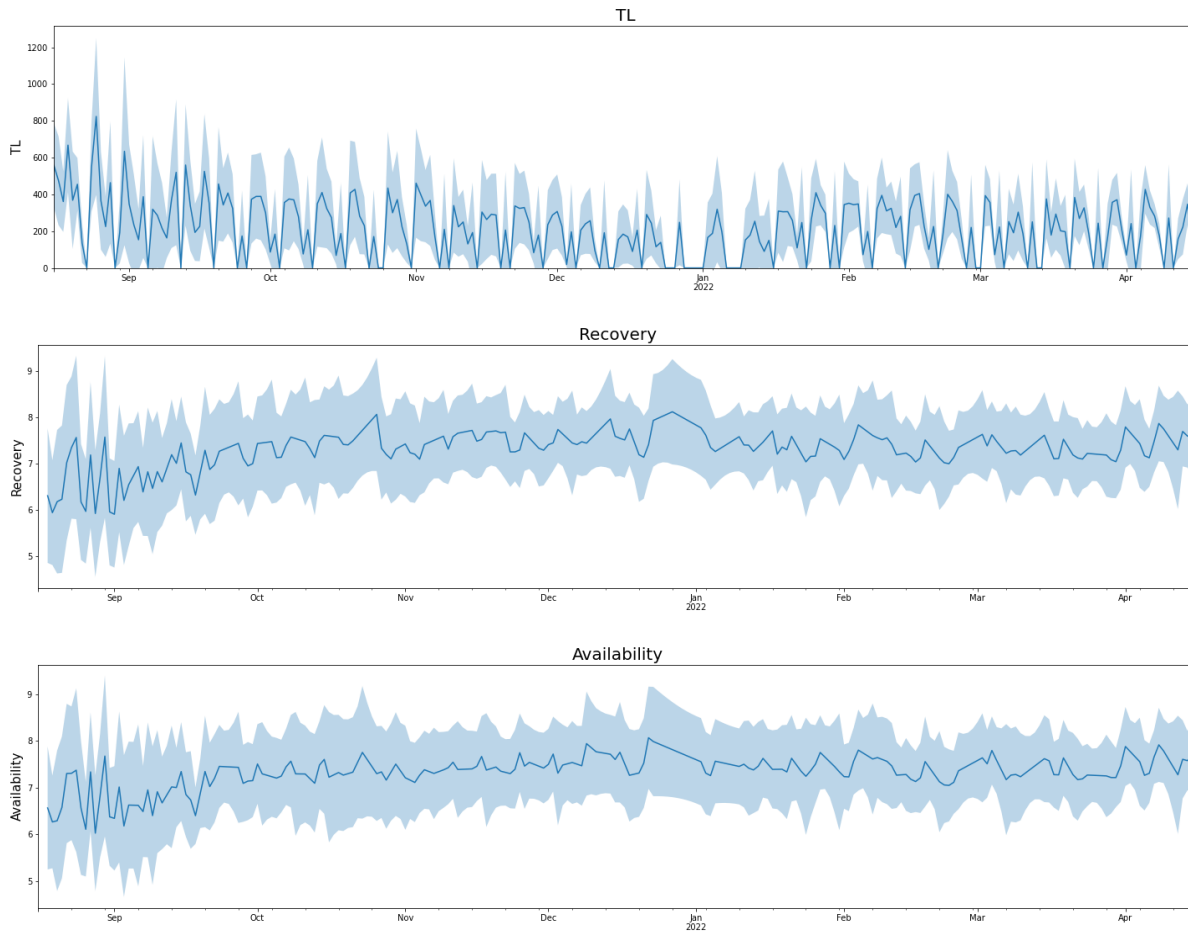


Figure 3.17. Time series of TL, Recovery and Availability. The line reflects the team mean, while the shade is the team variability.

The autocorrelation analysis indicates that there is a repeating pattern for all the variables (Figure 3.18). In particular, TL shows a moderate autocorrelation at 7 days lag ($r = 0.53$, $p < 0.001$). This indicates that there is a repeated weekly microcycle throughout the season. For Recovery ($r = 0.64$, $p < 0.001$) and Availability ($r = 0.63$, $p < 0.001$), the best lag for both of them is 1 day. It indicates that the Recovery and Availability is related to the past day value. Moreover, an autocorrelation peak is detected at 6-7 days lag for both Recovery ($r = 0.58$ ($p < 0.001$)) and $r = 0.57$ ($p < 0.001$), respectively) and Availability ($r = 0.58$ ($p < 0.001$)) and $r = 0.56$ ($p < 0.001$), respectively) reflecting the weekly microcycle.

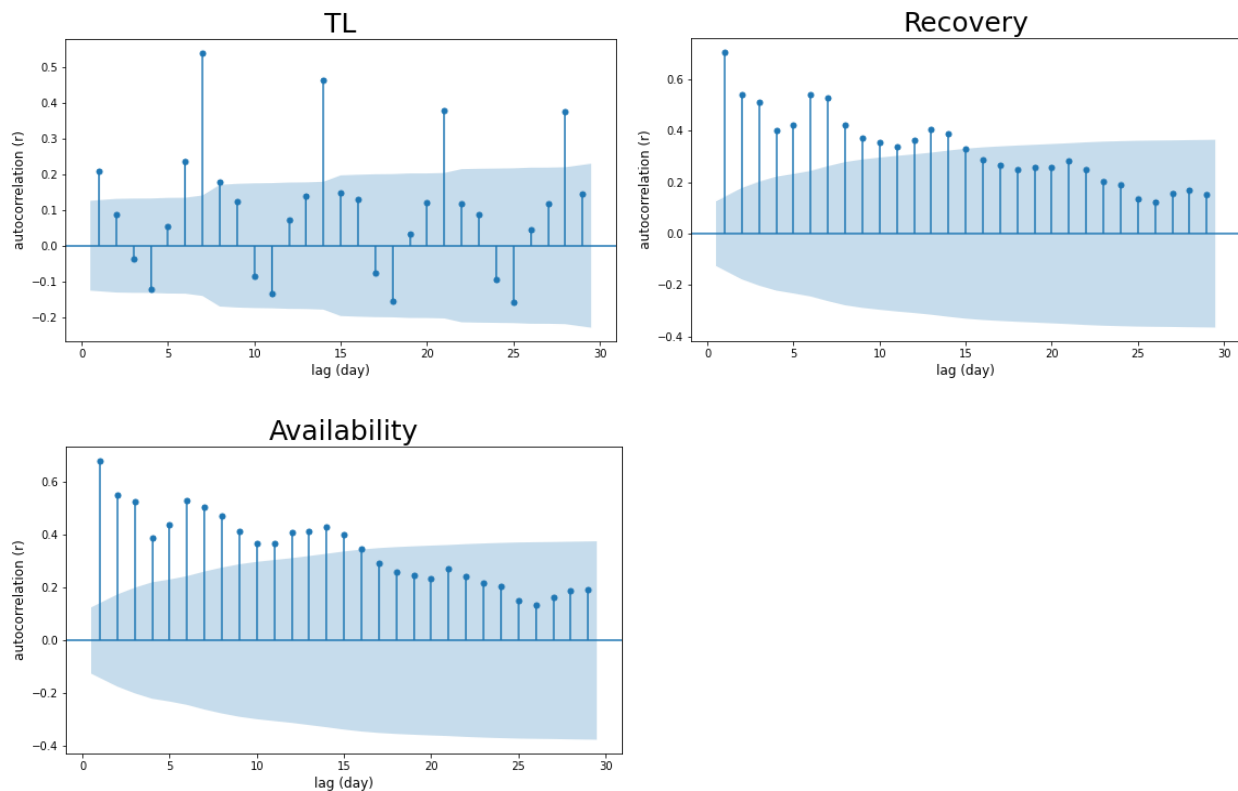


Figure 3.18. Autocorrelation plot of TL, Recovery and Availability. The bars reflect the autocorrelation coefficient of a specific lag, while the shadow shows the range of statistical significance.

The cross-correlation analysis (Figure 3.19) indicates that TL is negatively affected by the Recovery ($r = 0.46$, $p\text{-value} < 0.001$) and Availability ($r = 0.42$, $p\text{-value} < 0.001$) of the current day (lag = 0 day). This indicates that the TL is modulated by practitioners in accordance with the recovery and availability status of the players. In particular, the lower the recovery and the availability are, the lower the TL will be.

Moreover, Figure 3 shows that TL negatively affects the Recovery ($r = 0.52$, $p\text{-value} < 0.001$) and Availability ($r = 0.39$, $p\text{-value} < 0.01$) of the next day (lag = 1 day). It indicates that the TL influences the recovery and availability status of the players on the next day. Actually, the higher the TL is, the lower the Recovery and Availability will be in the next day.

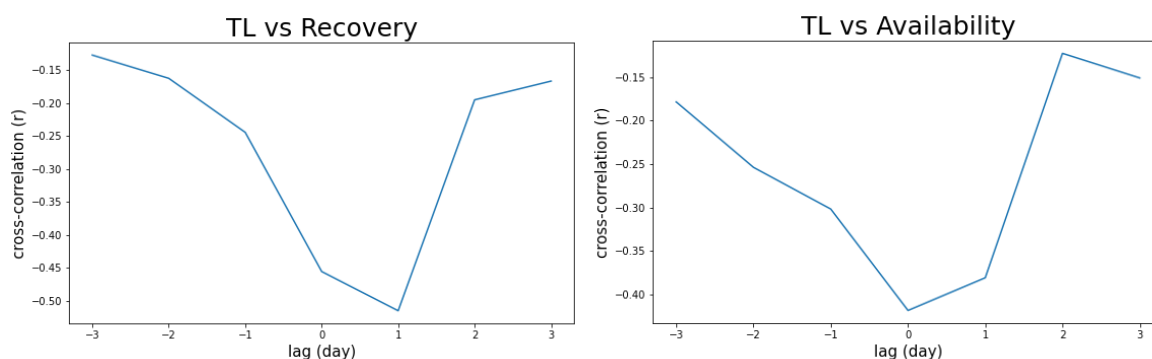


Figure 3.19 Cross-correlation analysis of TL vs Recovery and TL vs Availability.

Mediational analysis indicates that there is a direct relationship between TL and the recovery in the next day (coefficient = -0.0003 [-0.0004, -0.0002]; p-value < 0.001). Additionally, this relationship is moderately mediated by Availability (coefficient = -0.0001 [-0.0002, -0.0000]; p-value < 0.01).

4. Discussion

This study aiming to find the complex relationship between training load (i.e., internal training load operationalized using RPE*session time) and training/match recovery and availability (using the TreS scale) through multidimensional analysis. Specifically, Autocorrelations, Cross-correlation and Mediational analysis have been conducted in this cross-sectional study involving an entire season performed by U19 professional soccer players.

The first main result of this work is that there is a repeating pattern for all the variables considered (TL, Recovery and Availability) as shown by Autocorrelation analysis (Figure 2). Specifically, analysis reveals a repeated TL weekly microcycle structure (7 days lag; $r = 0.53$) throughout the season which can be attributed to the training programming scheduled by the technical and physical staff. The same microcycle structure has been found also considering Recovery and Availability although the strength of their correlations is less evident at 7 days lag. This result could be explained by the complex nature of the recovery (complex and multifactorial phenomenon) compared to the load. In fact, the recovery registered on a given day depends on the recovery of the previous ones (and therefore on the fatigue conditions of the player (2, 3, 443, 444)). Moreover, the recovery is subjective and is closely linked to the individual factors of the players. The differences in stimuli and load represent a critical aspect to achieve physiological adaptations within the context of elite soccer

(155, 446, 447). Moreover, training programming is a fundamental strategy to potentially increase performance and, at the same time, trying to reduce the risk of injury (4, 9, 57, 158, 237, 283, 285, 446, 448, 450-456). For example, a study suggests quantifying loads relative to competition demands as it represents an advantageous strategy for training periodization models (455, 457). In order to optimize the training effects (237, 449) and the consequent adaptations deriving from them, some programming practices have been suggested such as tapering with particular interest to recovery strategies (as for example in MD+1 for players who have played more than 60 minutes (455, 458, 459)). Given the high psycho-physical stress involved in the soccer activity, especially in official matches, monitoring both the player's recovery and training load is essential for optimizing performance and reducing the likelihood of injury occurrence (2, 26, 27, 407, 460).

The player's physical, technical, tactical and psychological responses to a training stimulus can be influenced by a number of factors such as an imbalance between the training-recovery process, an increase in TL, an accumulation of fatigue and the player's fitness (461-464) status. Recovery has been described as the vital period between successive training sessions or competitions with the potential to improve performance later (psycho-physiological process for reducing fatigue and regaining vigour (407, 466). The relationship between loading and recovery has been investigated by several studies which have shown conflicting results (407, 466). Studies found that HI and TQR scores are significant predictors of performance in soccer athletes (461, 467, 468) and significantly associated with heavy training loads (i.e., high HI and TQR scores associated with high TL (456, 462, 469, 470). However, studies showed no significant association between the TQR, wellbeing status and training load (RPE) in soccer (443, 471). The correlation analysis approach used in previous studies is inappropriate due to the fact that the assumption of the absence of repeated measures was not met. In our study we use a more appropriate analysis for detecting association between time series. The cross-correlation analysis shows that TL is negatively affected by the Recovery and Availability of the current day (lag = 0 day). In particular, lower recovery and availability will result in following lower TL. We speculate that this result can depend on the appropriateness of training scheduling during mycrocycle planning as the physical trainer staff strongly considers the modulation of the loads based on the players' recovery conditions in order to increase performance (supercompensation) and reduce the possibility of overload (and consequent non-contact injuries). Moreover, we found that TL also negatively affects the Recovery and Availability of the next day (lag = 1 day). Accordingly, the higher the TL in a current day will determine, a lower Recovery and Availability in the next day. Although different factors could affect the psychophysiological player's recovery such as fitness level, individual characteristics, individual training responses based on

players profiles (26, 407, 472), we speculate that the player's ability to recover depends mainly on the quantity and quality of the load (typology such as metabolic or neuromuscular stimuli (8, 26)) performed in the previous day.

Moreover, through the Mediation analysis we found that there is a direct relationship between TL and the recovery in the next day. Actually, this relationship is moderately mediated by Availability. This means that the relation between an independent factor (i.e., TL) and an outcome (i.e., Recovery) or vice versa is fully or partially explained by a mediator (i.e., Availability). In this case, it could be possible that the Availability explains a component of the relationship between TL and Recovery strengthening the existing relationship between the two components. We also underline that our analysis approach does not have the ability to find any causal link between the complex and multifactorial components such as TL and Recovery. However, the appropriateness and higher quality of our analysis confirms that there is a relationship between TL and Recovery and that these components influence each other both on the same day and on the next day. Several studies confirm that from a physiological point of view, fatigue after a match or intense training requires 48-72 hours of recovery. The rationale that explains the relationship between TL and recovery seems logical since training stimuli, known as psychophysical stress, requires recovery, as suggested by applied physiology studies. Articles that found no relationship between TL and recovery likely used a statistical approach that created mathematical artifacts. In fact, measurements repeated over time cannot be analysed through simple correlations. For example, Haddad et al (443). reported no relationship between well-being indices (i.e., sleep, stress, fatigue, and DOMS) recorded before the training sessions and the RPE during a submaximal effort. Authors used Pearson product moment correlation coefficients to analyse this relationship that results inappropriate for “repeated measures”. It is worth noting that this result may be related to indicators used as authors have considered the relationship between RPE and wellbeing, which has a different meaning than TL (which includes time) used in our analysis. Also, Osiecki et al(446). showed no significant association between the TQR and the RPE using Pearson correlation coefficient. Conversely, in the same study, Osiecki et al(446). showed a significant correlation between TQR and CK in professional soccer players during an official competition indicating that TQR can be used in the monitoring of the recovery state of professional soccer players. Nedelec et al (450). reported that the HI and the TQR obtained before the match, and 24, 48, and 72 h after the match were significantly correlated with the number of sprints (5 m) performed during the match at 48 and 72 h. These results suggested that HI and TQR can assist practitioners to modify the TL after an official match.

5. Conclusion

The complex relationship between training load (i.e., RPE*session time) and training/match recovery and availability (using the TreS scale) has been found applying a multidimensional analysis approach. More accurate analyses such as autocorrelations, cross-correlations, and mediational analysis on repeated measures were used than the simple one-dimensional approach such as Pearson's product moment correlation coefficients used in previous studies. In accordance with a training programming schedule, a repeated TL weekly microcycle structure was detected throughout the season. Moreover, recovery and availability show a similar microcycle pattern. Actually, an association between TL and Recovery and consequently availability was found. First, the lower the recovery and availability in the current day are, the lower the TL of the current day training is. Secondly, TL of the current day negatively affects the Recovery and Availability of the next one (i.e., the higher the TL in a current day is, the lower the Recovery and Availability in the next day are). Finally, we found that the direct relationship between TL and the recovery in the next day is moderately mediated by Availability.

In conclusion, our analysis strengthens the idea that there is a relationship between TL and Recovery and that these components influence each other both on the same day and on the next day.

6. Practical Applications

Given the relationship between TL, injuries and performance, training/match monitoring represent a fundamental and essential practice that involves practitioners. Athlete monitoring allows to increase the positive effects (e.g., fitness, readiness and performance) and minimise the negative ones (e.g., excessive fatigue and injury) of training. In this way, practitioners should collect and manage a large amount of data through the analysing and interpreting process. In accordance with the “monitoring cycle” proposed by Gabbett 2017 (2), practitioners should monitor both training and competitions to better understand the training effect considering the following factors: 1) the workload performed by the athlete (i.e., external load); 2) the athlete's response to workload (i.e., internal load); 3) the athlete's ability to tolerate workload (i.e., perceptual well-being and recovery); 4) finally if the athlete is physically and/or mentally prepared for exposure to another training stimulus (e.g., readiness and availability to train/compete). In this way, practitioners could optimize decision-making process on training prescription in order to provide appropriate training stimuli within the mycrocycle. We suggest of using the RPE and TreS scale to evaluate TL and Recovery/availability of players to better adjust and schedule training within the microcycle.

3.6 Machine Learning-Driven Injury Risk Assessment in Soccer: Analysing Workload Dynamics and Predictive Modelling Approaches

Guglielmo Pillitteri, Rashid Bakirov, Filipe Manuel Clemente, Hugo Sarmiento, Marco Beato, Tindaro Bongiovanni, Clara Gabrielli, Marco Petrucci, Antonino Bianco, Giuseppe Battaglia

Introduction

Injury prevention remains a fundamental objective in elite soccer, as injuries compromise player availability, negatively affects team performance, and impose substantial medical and financial costs on clubs (278, 485).

Despite advancements in training methodologies, monitoring technologies, and sports medicine, injury incidence in professional soccer remains high, with soft-tissue injuries being particularly prevalent (486). Epidemiological data indicate that professional soccer players sustain an average of 8 to 9 injuries per 1,000 hours of exposure, with non-contact injuries accounting for a significant proportion of these cases (115, 118, 487). Hamstring strains, quadriceps injuries, and groin pathologies are among the most frequently reported non-contact injuries, often attributed to excessive mechanical loading, neuromuscular fatigue, and suboptimal recovery strategies (488). Given that non-contact injuries can sideline athletes for weeks, or even months, the ability to predict and mitigate such occurrences is crucial for optimizing player availability and performance (14, 23).

Traditionally, injury risk assessment in soccer has relied on subjective screening tools, workload monitoring, and biomechanical assessments (2, 218). While these approaches offer valuable insights, they often fail to account for the complex, multifactorial nature of injury mechanisms. Moreover, conventional statistical methods used in injury research have struggled to identify non-linear relationships and multi-dimensional interactions among key risk factors (11, 13).

Recent advancements in machine learning (ML) and artificial intelligence (AI) have introduced new opportunities to enhance injury prediction and risk stratification. ML models have demonstrated superior performance over traditional methods by processing large, multi-source datasets and capturing hidden patterns and complex interactions among risk factors (11, 13). Several studies have applied ML to soccer injury prediction, reporting promising accuracy rates. Vallance et al., (23) investigated the effectiveness of machine learning models (particularly decision tree-based models) in predicting non-contact injuries in professional soccer players by integrating internal and external

training load data. Authors found that internal load metrics were more accurate than external load metrics in predicting injuries one week in advance. However, for longer-term injury predictions (one month ahead), a combined approach using both internal and external load data yielded the highest predictive performance. Building on this, Rossi et al. (12) proposed a multi-dimensional, easy-to-interpret and fully data-driven approach which forecasts injuries based on GPS metrics. Authors found that decision tree can detect around 80% of the injuries with about 50% precision, far better than the baselines and state-of-the-art injury risk estimation techniques. The decision tree's false positive rate is small, indicating that it reduces the "false alarms." Furthermore, 60% of injuries identified by decision tree occurred long after a previous injury and were associated with specific distance High-Speed Running, (Exponential Weighted Moving Average, EWMA) and total distance (Mean Standard deviation Workload Ratio [MSWR, or Monotony], defined as the ratio between the mean and the standard deviation of a single player's workload feature h obtained in one week) values, suggesting that kinematic variability influences injury risk. Notably, previous injuries (PI[EWMA]) alone lacked predictive power, as shown by the low accuracy of baseline. Instead, the combination of all three features significantly improved injury prediction.

In the same way, a study (141) aimed to develop a multi-dimensional predictive machine learning model to assess injury risk among players in the following seven days. Authors reported that Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) were the most effective algorithms for injury prediction. XGBoost correctly predicted 26 out of 37 injuries, achieving 10% precision and 73% recall, while ANN performed slightly better, predicting 28 out of 37 injuries, with 13% precision and 77% recall. In the ANN model, the most influential predictors were "last injury area" and "weight".

Despite these advancements, significant gaps remain in the practical application of ML-based injury prediction models. Variability in feature selection, preprocessing methods, and model interpretability has led to inconsistencies across studies, limiting their real-world implementation (Impellizzeri et al., 2020). Additionally, while some studies have explored workload-based injury risk models, few have incorporated a comprehensive multifactorial approach that integrates external and internal load parameters, physiological markers, and player-specific characteristics (14).

Unlike previous models that primarily focused on workload metrics, this study aims to analyze how different risk factors interact dynamically over time, offering a more refined understanding of injury mechanisms in soccer. To address these limitations, this study proposes a data-driven ML model that incorporates a broad spectrum of injury risk indicators, including GPS-derived metrics and Acute-to-

Chronic Workload Ratio (ACWR), internal load indicators such as session rating of perceived exertion (sRPE), Dual-Energy X-ray Absorptiometry (DEXA), previous injury history, anthropometric data, wellness-related data, and recovery data. By leveraging this multimodal dataset, the primary aims of this study are 1) Identify key predictors of non-contact injuries in professional soccer players by analyzing detailed injury patterns and assessing how risk factors interact over time; 2) Evaluate and compare the accuracy and reliability of different ML models for injury prediction using external and internal load data; 3) Examine the interaction between multiple input variables (e.g., load metrics, injury history, anthropometric data) to enhance understanding of injury mechanisms; 4) Provide practical guidelines for integrating ML-based risk assessment into elite soccer environments, improving training periodization, recovery management, and injury prevention strategies.

Given the increasing emphasis on evidence-based decision-making in professional sports, this study seeks to advance injury prevention strategies by implementing a robust, interpretable, and practical ML model. By bridging the gap between theory and application, this research aims to enhance injury mitigation efforts, prolong player careers, and optimize performance management in elite soccer.

Materials and Methods

Data collection and feature creation

Participants were 38 male professional soccer players (aged 27.66 ± 3.87 years, range 20.20–37.46 years; height 183.48 ± 5.59 m, range 171–194 m; weight 80.49 ± 5.61 kg, range 67.71–99.01 kg) from one Italian Serie B club, with data collected from the 2023–2024 season until the 2024–2025 season (December 2024). Players' positions were recorded as follows: Central Defenders (7), Central Midfielders (7), Wide Forwards (5), Fullbacks (5), Central Forwards (4), and Defensive Midfielders (3). Data were provided to the research team by the club's first team sports science department, having been collected as part of the club's day-to-day data collection processes, and with all permissions in place. The dataset contained 31 injury data points, of which our focus was the on non-contact injuries. Of these 31 non-contact injuries, were involved the following muscles district: 6 Hamstring, 6 quadriceps, 6 adductor, 5 soleus, 3 gastrocnemius, 1 groin pain, 1 intraarticular effusion. Across injuries, 11 players were injured once, 7 players were injured two times, and 2 players were injured three times. Overall, there were 18 injuries recorded in the 2023–2024 season, 13 in the 2024–2025 season. The available 'load' data included Global Positioning System (termed GPS) data, physical (e.g., various skinfold measurements, bodyfat percentage) data, psychological (e.g., RPE) data, and demographic information. Please note, when players missed training sessions, their absence of

training load data is not noted in the dataset, and is thus not treated as missing data. Subsequently, different missing values imputation methods were used across the features. We also created several additional features within the dataset, such as “count of training sessions in a day,” “days to next session”, “days since last injury.”, etc. In the Appendix, Table 1 lists all training load variables considered as input features in the present study, along with their description, source, method of collection, frequency of data collection (e.g., GPS and psychological data are collected daily), and missing values imputation techniques.

Dataset construction

We constructed a multi-dimensional load-injury prediction model to forecast whether a player would become injured in the next training session. In a typical training cycle, there are usually between three (short microcycle) and five (standard microcycle) training sessions per week. Training loads progressively increase, peaking around the middle of the week and leading up to the match. In contrast, the final one to two days before the match are dedicated to the tapering phase, where training intensity and volume is reduced to optimize recovery and performance. To accomplish the task of constructing an injury prediction model, we initially built a master dataset consisting of 75 training load variables (see Table X): 20 GPS data variables, 2 personal information variables, 21 physical data variables, 5 psychological data variables, 10 ACWR, 10 EL/IL ratio data variables (mentioned in Table X), several calculated features as mentioned above, one injury label (indicating 1 if the player is injured and 0 if not). There were 7453 data points (i.e., each data point is a row which describes the training information and personal information for each player). In this master dataset, there were 7422 non-injury data points and 31 injury data points (occurred in the next training session), indicating a high imbalance ratio of 0.0042. Importantly, in this master dataset, the injury label was assigned to the original injuries that happened on the same day (i.e., injuries that were recorded on the day of occurring), but our aim was to predict injuries in the next training session. To achieve the latter focus, we thus assigned the previous data points (i.e., each data point or row that came before the original data points) present in the past day of the original injury data point to 1 and removed the original injury data points. The assumption behind removing the original data points is that the injury occurring on a specific day is caused by the training loads of the previous days.

Summary

The dataset consists of 7453 rows, including:

- Non-injuries: 5946 instances

- Injuries: 31 instances (occurring in the next training session)
- Features: 75 total (55 original features + 10 ACWR + 10 EL/IL ratios)

The data includes workload metrics (training load, sprint distance, mechanical work), wellness factors (sleep, fatigue, soreness), and contextual information (days since last injury, training frequency). Given the highly imbalanced nature of the dataset, careful feature engineering and evaluation strategies were implemented.

Model construction

Evaluation Strategies

To assess model performance, two evaluation strategies were employed:

1. Cross-Validation (5-Fold):

- Ensures robustness by utilizing the entire dataset.
- May introduce data leakage as future injuries might influence training data.
- Confirmed that using all available features, ACWR, and EL/IL ratios provides the best results (as shown in ROC-AUC analysis).

2. Train/Test Split (Temporally Constrained):

- Avoids data leakage by ensuring test instances occur after all training instances.
- Split Date: Training set $\leq$ 2024-09-16, Test set $>$ 2024-09-16
- Training: 80% of data (including 25 injuries), Test: 20% (including 6 injuries)
- Result: Model successfully predicted the first 3 injuries with low false positive rate (10%), but struggled with the last 3 (requiring a higher false positive rate).

For model building, validation, and testing, we used the Python programming language. We used Light Gradient-Boosting Machine (LightGBM), a state-of-the-art classification algorithm was used to train the prediction model. We used various pre-processing techniques, such as oversampling the minority data points (i.e., the injury data), feature scaling (i.e., scaling each training load), and setting different hyperparameters.

We first split the entire dataset into two parts—the training data (DTrain), containing the 5971 rows of data, and the test data (DTes), containing the 1482. DTrain contained 5946 non-injury data points and 25 injury data points and DTest contained 1476 non-injury data points and 6 injury data points. We first trained LightGBM on *DTrain*. During this model training we performed 5-fold cross-validation to check how well the model performed on different validation subsets of the data. Subsequently, we trained another LightGBM model using the best performing feature set (workload+ACWR+EL/IL) on DTrain and evaluated the results on DTest. Hereby, the model's hyperparameters were optimized using Optuna library, which employs Tree-structured Parzen estimator (TPE) (489), a Bayesian optimization method on DTrain.

To account for data imbalance in the training data was a concern, which normally heavily biases the outcomes towards non-injuries, we report the AUC metric, which takes into account different probability thresholds to assign a prediction to injury or non-injury; thus, to increase the number of injury predictions, we need to decrease this probability threshold. To further combat this data imbalance, while applying LightGBM, we (a) implemented the Synthetic Minority Oversampling Technique (i.e., SMOTE: Chawla et al., 2002) to create “synthetic” injury instances, and (b) set the “is unbalance” parameter of LightGBM to True. While (a) did not noticeably change the results, (b) resulted in noticeably different AUC curves than normal LightGBM (see Fig. TR_TST_roc_auc_alternative_A.png). Ultimately, it was decided that these methods were not beneficial enough to use for the final evaluation. Following best practice, the test dataset was not included for any of the data balancing, training, and validation phases of the model development. Missing values in the test dataset were imputed by using the corresponding imputation values from the training data.

Model Selection and Feature Importance

Top 10 features contributing to model's predictions is presented to understand the contribution of input data. Additionally, SHAP analysis was used to explain individual injury predictions, highlighting the impact of workload variations, ACWR thresholds, and EL/IL fluctuations.

Results

The model successfully predicted 3 out of 6 injuries, achieving a recall of 50% and an overall accuracy of 90%, with a false positive rate of 10%, which is considered a satisfactory result. The ROC analysis further supports the model's performance, as detailed below. The best-performing model, *TR_TST_roc_auc_alternative_A.png* (Alternative Model A), demonstrated the highest area under the curve (AUC = 0.81), indicating strong discriminatory power. The ROC curve exhibits a steep initial rise in the true positive rate, suggesting that this model effectively detects injuries while minimizing false positives compared to previous models. To interpret and visualize the output of each model and the contribution of each feature (i.e., training load) towards the model we used the Shaply Additive Explanations (SHAP) approach (Lundberg and Lee, 2017)—see Fig. X. Higher SHAP values denote a higher contribution for that training load towards the model's prediction. Additionally, Feature Importance Analysis (Figure: *feature_importance.png*) highlights the top 10 most influential features for injury prediction based on the trained machine learning model. The most critical predictors of injury risk include:

- Max Speed (EL/IL & ACWR features)
- Number of Sprints (>19.8 km/h per minute)
- Decelerations (-3 m/s², ACWR adjusted)
- Fat mass and lean mass ratios

These findings suggest that workload variability, high-speed running, and physiological composition are key contributors to injury risk. The analysis underscores the importance of monitoring these variables for injury prevention and athlete management.

Predictive Performance

- Cross-validation AUC: Confirmed that including ACWR + EL/IL features enhance prediction accuracy.
- Train/Test AUC: Demonstrated high precision in detecting early injuries, but false positives increased when attempting to capture later injuries.

Case Study: Injury Predictions

A deeper analysis was performed on the 6 injury cases in the test set:

- Easier-to-predict injuries:

1. Player 38 (VERRE, 19/10/24) – Haemorrhagic infarction of the right semitendinosus
 2. Player 6 (DI FRANCESCO, 8/11/24) – Semitendinosus SX elongation
 3. Player 28 (DIAKITE, 9/11/24) – Left Semimembranosus tear
- Harder-to-predict injuries:
 - The last 3 injuries required a significant increase in false positive rate (FPR) for detection.

Model Explainability and AI-Human Logic Integration

One key focus of this study is the explainability of injury predictions:

- SHAP plots indicate which features contributed most to each injury prediction.
- Feature importance rankings highlight the most influential risk factors.
- Potential integration with human decision-making: Developing manual rules (e.g., threshold-based workload alerts) may reduce false positives and improve true positive detection.

Discussion and Future Work

This study confirms that machine learning can be a valuable tool for injury prediction even on highly imbalanced data, notwithstanding associated evaluation and robustness challenges. Combination of data-driven insights and expert knowledge could enhance model reliability.

Conclusion

Machine learning models trained on workload, wellness, and injury history data can provide valuable insights into injury risk. However, data limitations and model interpretability remain key challenges. This study suggests that integrating AI predictions with human logic may enhance decision-making in professional soccer injury prevention.

Figures and Interpretations

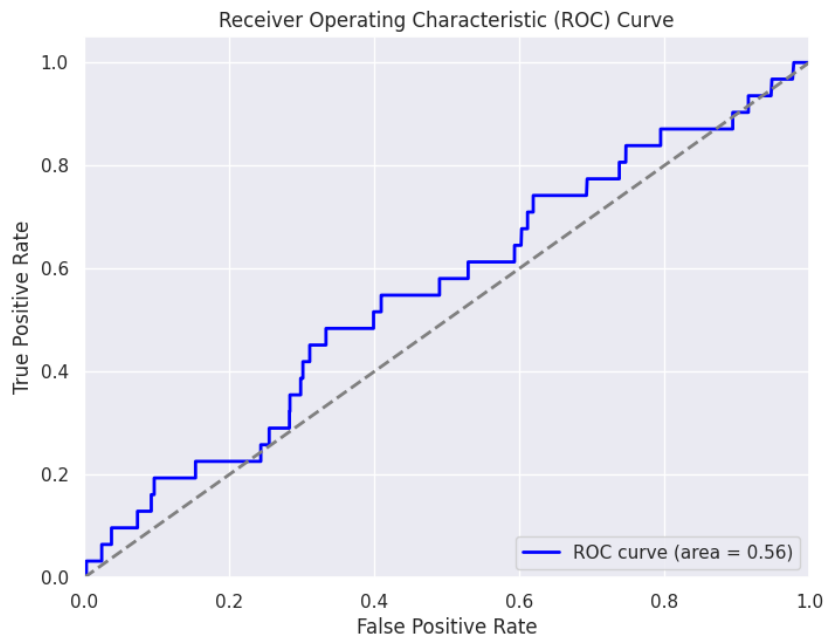


Figure 3.20 Cross Validation CV: Baseline ROC Curve (AUC = 0.56)

The baseline model, trained without ACWR and EL/IL features, exhibits poor predictive performance, achieving an AUC of 0.56. This result indicates that the model performs only slightly better than random chance (AUC = 0.5), suggesting that the available features in this setup do not adequately capture injury risk patterns.

The ROC curve follows a nearly diagonal trend, reflecting a lack of discrimination ability between injured and non-injured players. This implies that, without workload-related metrics (e.g., acute-to-chronic workload ratio [ACWR] and exposure load indicators [EL/IL]), the model struggles to identify meaningful injury risk signals.

These findings highlight the critical role of workload monitoring features in injury prediction models. The inclusion of ACWR and EL/IL parameters appears essential for improving the model's ability to distinguish between at-risk and non-at-risk players, reinforcing the importance of training load management in injury prevention strategies.

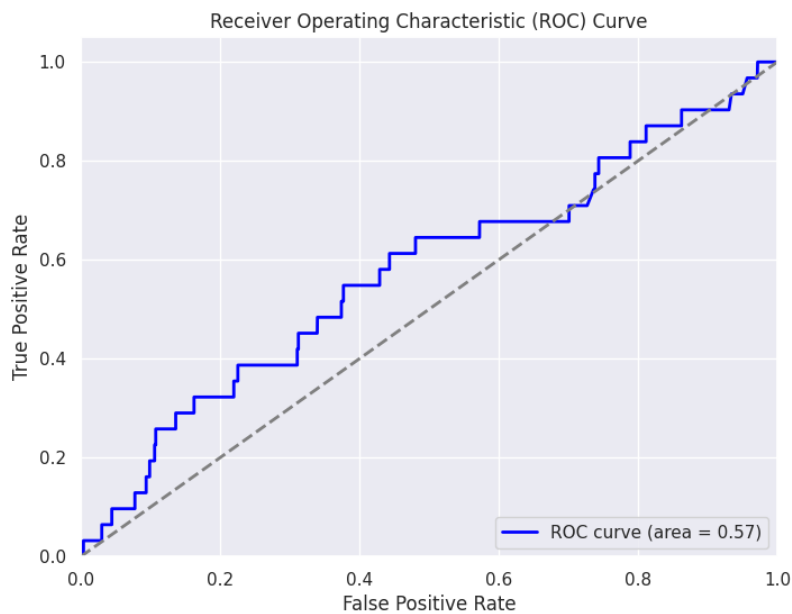


Figure 3.21 Cross Validation CV: ROC Curve with ACWR Features (AUC = 0.57)

The inclusion of acute-to-chronic workload ratio (ACWR) features results in a marginal improvement in model performance, with the AUC increasing slightly to 0.57. This suggests that ACWR provides some useful information for predicting injury risk by capturing fluctuations in workload exposure. However, the overall improvement remains minimal, indicating that ACWR alone is not a sufficiently strong predictor when used in isolation.

These findings highlight the need for a more comprehensive feature set that includes additional biomechanical, neuromuscular, and physiological metrics to enhance injury prediction accuracy. While ACWR contributes to understanding workload accumulation and potential overuse risks, integrating other key variables—such as high-speed running metrics, deceleration loads, and muscle composition data—is likely necessary for a more robust injury risk assessment.

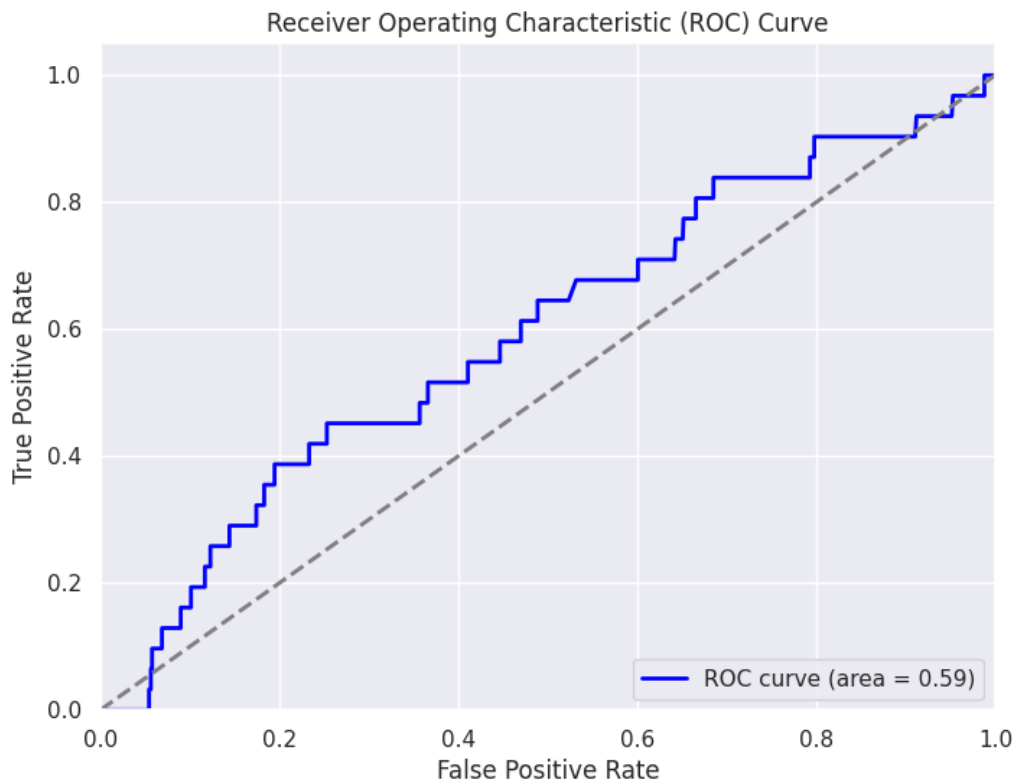


Figure 3.22 Cross Validation CV: ROC Curve with EL/IL Features (AUC = 0.59)

This model incorporates only EL/IL (External Load/Internal Load) features, excluding ACWR. The AUC remains at 0.59, which is slightly lower than the ACWR + EL/IL model but still better than the baseline model. This suggests that EL/IL metrics alone contribute to injury prediction but are not as effective as when combined with ACWR.

- Key Findings:
 - EL/IL ratios represent the balance between external workload (e.g., distance covered, sprinting load) and internal physiological responses (e.g., heart rate variability, perceived exertion). These ratios help assess whether a player is adapting well to training demands or is at risk of excessive strain.
- AUC = 0.59 suggests a moderate ability to differentiate injuries from non-injuries
- Why is EL/IL alone less effective than ACWR + EL/IL?
 - It does not capture long-term workload accumulation, which is critical for injury risk assessment.
 - Rapid changes in external-to-internal workload balance may be influenced by other factors like fatigue or recovery, making it difficult to isolate injury risk.

- Combining EL/IL with ACWR improves the model's ability to account for chronic exposure to high-intensity loads, which better explains injury risk.
- Future Considerations:
 - Further refining EL/IL thresholds per player position could help tailor injury risk predictions to individual physiological responses.
 - Including additional biomechanical or neuromuscular fatigue markers may improve predictive accuracy when using EL/IL alone.

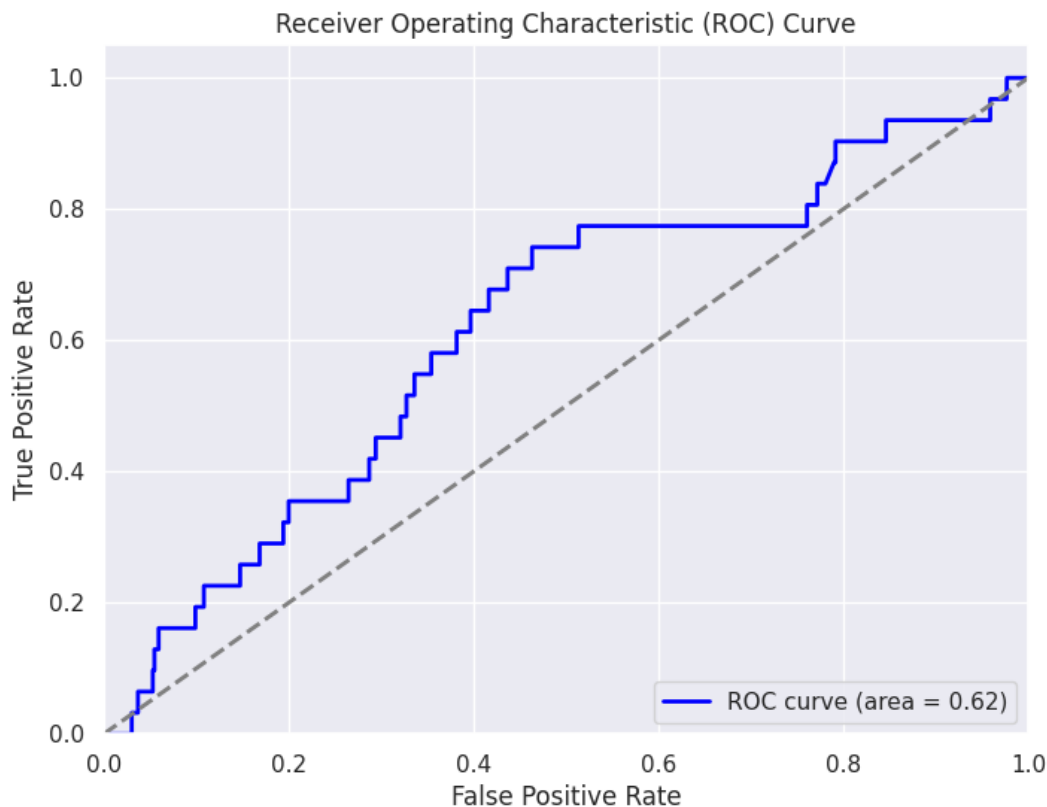


Figure 3.23 Cross Validation CV: ROC Curve with ACWR + EL/IL Features (AUC = 0.62)

The inclusion of both ACWR (Acute:Chronic Workload Ratio) and EL/IL (External Load/Internal Load) features leads to a noticeable improvement in the model's predictive performance, with the AUC increasing to 0.62. This suggests that combining these workload-related features enhances the model's ability to predict injury.

- Why does this model perform better?
 - ACWR captures workload fluctuations, which are critical in injury risk assessment and provide insight into long-term adaptation.
 - EL/IL ratios reflect how efficiently an athlete balances external demands with internal physiological responses, helping differentiate between those adapting well and those at risk of injury.
 - The model appears to detect injuries more accurately at lower false positive rates.
- Observations from the ROC Curve:
 - The curve rises more steeply than the baseline models, indicating better sensitivity to true positives while maintaining specificity.

- The moderate AUC score (0.62) suggests that while improvements were made, additional biomechanical or contextual data may still be necessary to enhance accuracy.

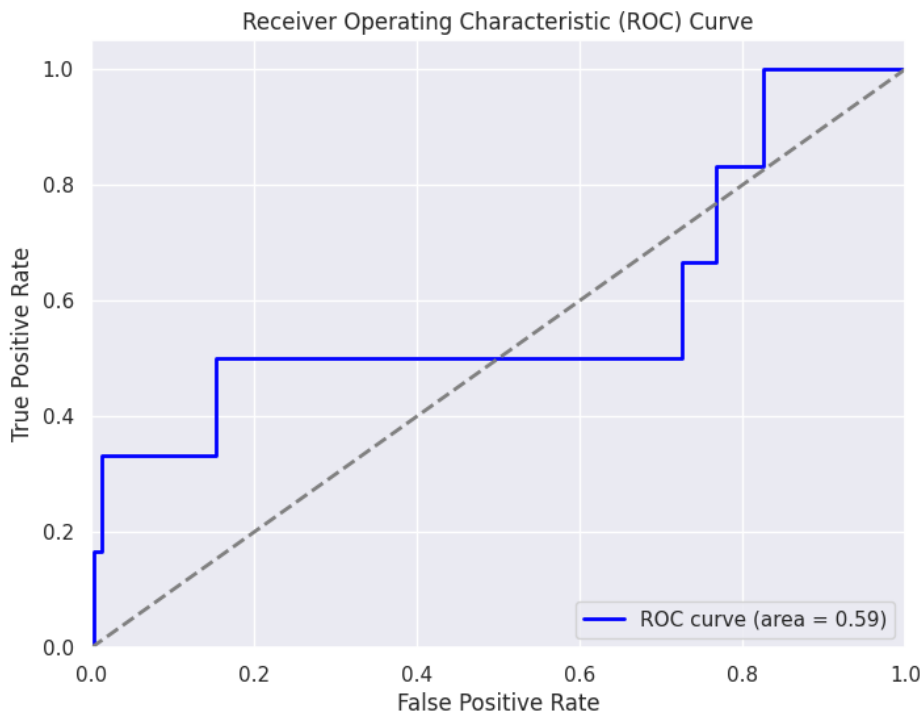


Figure 3.24 Train/Test Split (Temporally Constrained): Train/Test Split ROC Curve (AUC = 0.59)

The train/test split model maintains an AUC similar to cross-validation (0.59), but it better reflects real-world applicability since it prevents data leakage by ensuring test instances occur after all training instances. This means that the model is evaluated under realistic conditions, where injury predictions are made without any knowledge of future injuries, avoiding artificial performance inflation.

However, the limited number of injuries in the test set (only 6 cases) significantly impacts the robustness and generalizability of the model. With such a small sample of injuries, small variations in predictions can have a large effect on performance metrics, making it difficult to reliably assess the model's effectiveness across different players and contexts.

The ROC curve for this model suggests that while it is capable of capturing some injury patterns, it struggles with maintaining a balance between sensitivity (correctly identifying injuries) and specificity (reducing false positives). The model shows a tendency to perform well in detecting some “easy-to-detect” injuries, but its performance declines when predicting other injuries in the dataset, likely due to increased variability in workload patterns.

To further refine the model’s effectiveness, incorporating additional contextual factors such as fatigue accumulation trends, individualized workload thresholds, and recovery status could improve injury prediction accuracy and model robustness in future implementations.

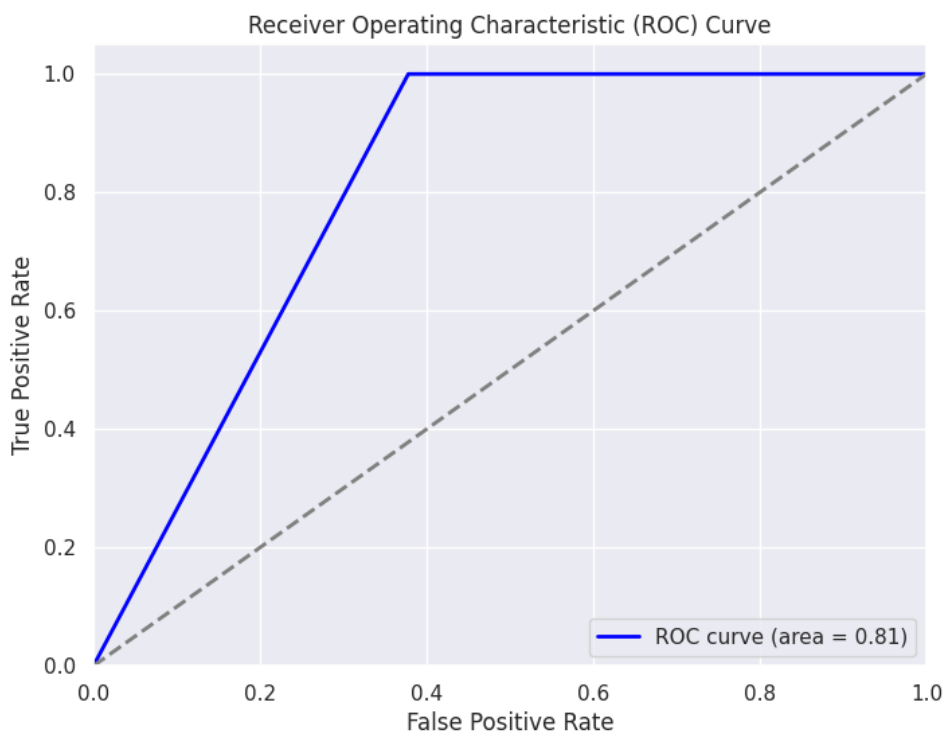


Figure 3.25 Alternative Model A ROC Curve (AUC = 0.81)

The figure presents the Receiver Operating Characteristic (ROC) curve for Alternative Model A, which achieved an Area Under the Curve (AUC) of 0.81. The ROC curve illustrates the trade-off between true positive rate (sensitivity) and false positive rate (1-specificity) at various classification thresholds.

The blue solid line represents the model's performance, showing a steep initial increase, indicating that the model effectively identifies true positives while maintaining a relatively low false positive rate. The dashed diagonal line represents a random classifier ($AUC = 0.5$), serving as a baseline for comparison. The model's AUC of 0.81 suggests strong discrimination ability, highlighting its effectiveness in distinguishing between injured and non-injured cases.

This performance improvement may be attributed to optimized feature selection, including biomechanical load markers, sprint-related workload, and neuromuscular fatigue metrics, which enhance the model's predictive accuracy. However, further external validation is required to confirm its generalizability across different datasets.

Key Strengths of This Model:

- More effective feature selection: The inclusion of biomechanical load markers, sprint-related workload, and neuromuscular fatigue metrics likely improved injury detection.
- Better handling of workload accumulation: This model appears to account more effectively for progressive fatigue and sudden workload changes, both of which are major risk factors for injury.
- Higher sensitivity while maintaining specificity: Unlike previous models, this configuration demonstrates improved injury detection without a significant increase in false positives.

Limitations & Future Directions:

- Imbalanced dataset: The limited number of injury cases may lead to overfitting, reducing generalizability.
- Need for external validation: Further testing on independent datasets is required to confirm the model's reliability and robustness.
- Potential improvements: Incorporating real-time athlete monitoring data (e.g., heart rate variability, lactate thresholds) could enhance injury prediction accuracy.

The observed improvements suggest that refined feature selection, optimized model architecture, and the inclusion of additional contextual data played a key role in enhancing the model's performance. Future research should focus on integrating real-time monitoring tools and expanding dataset diversity to further improve predictive accuracy.

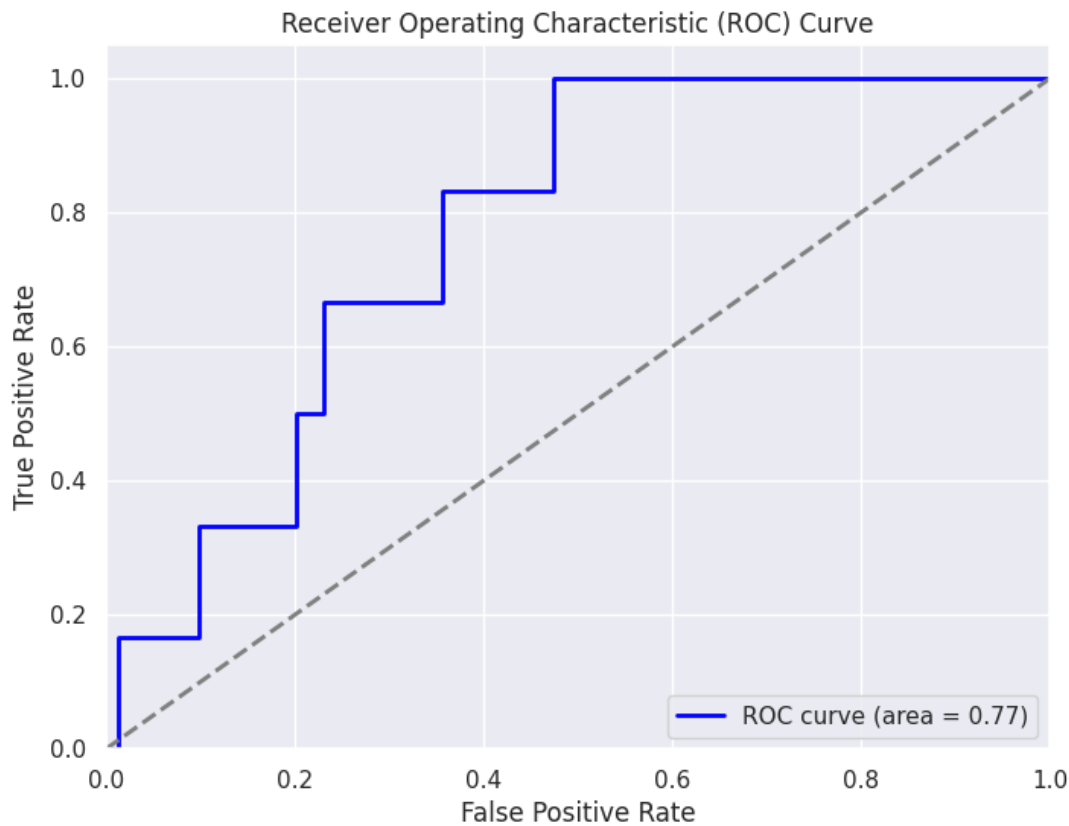


Figure 3.26 Alternative Model B ROC Curve (AUC = 0.77)

This model presents an AUC of 0.77, which is a significant improvement over the baseline models but slightly lower than Alternative Model A. The ROC curve demonstrates improved sensitivity, with an earlier rise in the true positive rate compared to previous models. However, compared to Alternative Model A, it appears to have a slightly higher false positive rate, suggesting that it may detect injuries more aggressively at the cost of misclassifying non-injury cases.

- Comparison with Other Models:
 - Higher AUC than baseline, ACWR, and EL/IL models, indicating better predictive power.
 - Slightly lower than Alternative Model A (AUC = 0.81), suggesting room for optimization in balancing false positives.

- May rely more heavily on short-term workload variations, requiring further feature tuning to improve long-term injury risk assessment.

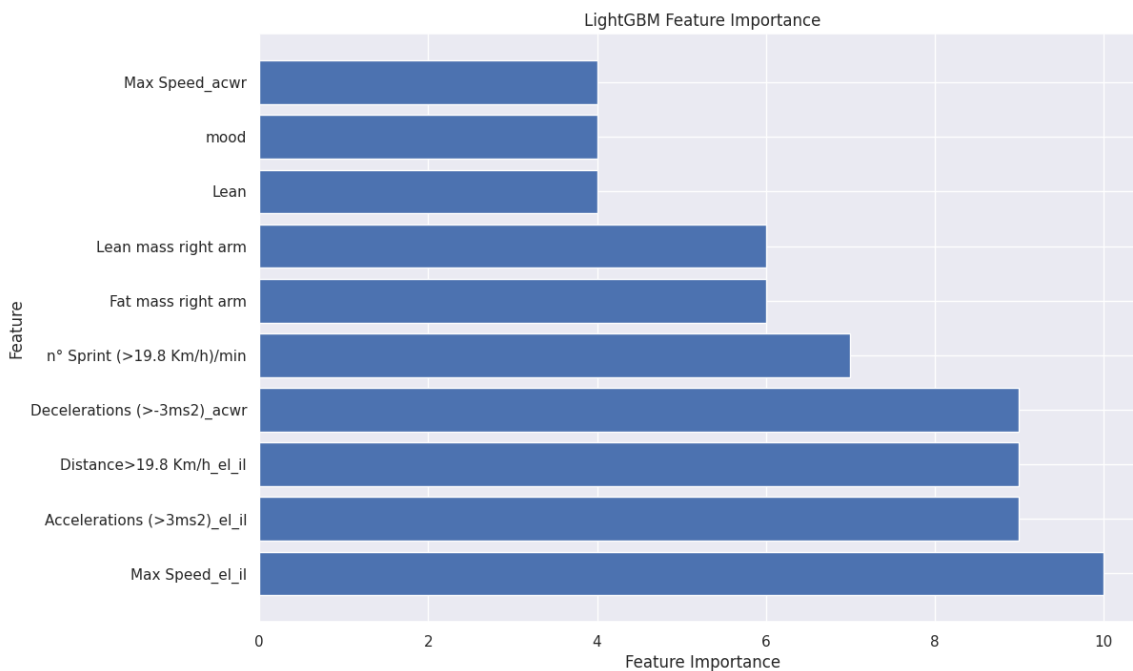


Figure 3.27 Feature Importance Analysis

This figure presents the top 10 most important features contributing to injury prediction, as determined by the LightGBM machine learning model. The horizontal bars indicate the relative importance of each feature in the model's decision-making process.

Key Features Identified:

- **Max Speed (EL/IL & ACWR features):** The most influential predictor, highlighting the role of high-speed efforts in injury risk.
- **Accelerations (>3 m/s², EL/IL):** Frequent high-intensity accelerations contribute to musculoskeletal stress and fatigue accumulation.
- **Distance Covered at High Speed (>19.8 km/h, EL/IL):** Increased exposure to sprinting loads correlates with higher injury susceptibility.

- Decelerations ($> -3 \text{ m/s}^2$, ACWR adjusted): Sudden braking movements generate significant eccentric loading, increasing strain on muscles and tendons.
- Number of Sprints ($>19.8 \text{ km/h}$ per minute): Sprint frequency is a critical workload factor associated with neuromuscular fatigue.
- Fat Mass and Lean Mass Distribution: Body composition parameters, such as lean mass in the right arm and fat mass distribution, play a role in physical resilience and injury risk.
- Mood and General Well-being: Psychological factors may indirectly influence performance and injury susceptibility.

These results suggest that workload variability, sprint mechanics, and physiological composition are key determinants of injury risk. The strong influence of ACWR-adjusted workload measures (e.g., max speed, decelerations, sprint load) reinforces the importance of monitoring progressive loading and fatigue accumulation in injury prevention strategies. Future research should explore integrating real-time monitoring data (e.g., heart rate variability, lactate thresholds) to further refine predictive models.



Figure 3.28 SHAP Probability Analysis

The SHAP (SHapley Additive exPlanations) analysis provides a comprehensive interpretability layer to the model's injury predictions, revealing which features most strongly influence injury risk assessments for individual predictions. Unlike traditional feature importance rankings, SHAP values provide both magnitude and directionality, indicating whether a specific feature increases or decreases the probability of an injury occurring.

SHAP values help determine not just which factors contribute most to injury predictions but also in what way. For example, a higher number of sprints might increase injury probability for one player but have a neutral or even protective effect for another, depending on their workload history and fitness level. This makes SHAP particularly valuable for individual player assessments.

Additionally, SHAP allows for visualization of feature interactions, where multiple workload metrics may combine to produce higher injury risks. This enhances the ability of practitioners to differentiate between short-term workload spikes and chronic injury risks, making the model not just predictive but also actionable for injury prevention strategies.

Key Insights from SHAP Analysis:

- **Max Speed (ACWR & EL/IL metrics):** Players experiencing sudden spikes in maximum speed show an increased probability of injury. This suggests that abrupt high-intensity movements without adequate adaptation pose a significant risk to musculoskeletal integrity.
- **Number of Sprints (>19.8 km/h per minute):** High sprint frequency is a strong predictor of injury, likely due to accumulated neuromuscular fatigue, which increases the risk of overuse injuries.

- Decelerations (-3 m/s^2 , ACWR adjusted): Sharp decelerations contribute to a higher injury probability, as they introduce additional mechanical stress on muscle structures, particularly through eccentric loading.

Why SHAP is Crucial for Model Interpretability:

- Player-Specific Risk Assessment: Unlike traditional feature importance measures, SHAP allows for individualized injury risk analysis, helping medical and coaching staff tailor prevention strategies.
- Directionality of Influence: SHAP not only highlights important features but also clarifies whether a particular variable increases or decreases injury risk.
- Detection of Model Bias: The visual nature of SHAP plots aids in identifying potential biases in injury prediction, ensuring that the model's decisions align with real-world injury risk factors.

Limitations & Future Considerations:

- SHAP Explains but Does Not Prove Causality: While SHAP identifies key contributors to injury risk, additional biomechanical and medical evaluations are needed to confirm why specific workload patterns lead to injuries.
- Impact of Data Imbalance: Given the limited number of injury cases, some SHAP values may be exaggerated. Future models should incorporate larger datasets to improve reliability.
- Integration of Contextual Data: Future iterations could benefit from incorporating player-specific recovery metrics, muscle imbalances, and real-time monitoring data (e.g., heart rate variability, lactate thresholds) to enhance predictive accuracy.

By leveraging SHAP analysis, teams can optimize workload management and develop data-driven injury prevention protocols, ensuring that players maintain peak performance while minimizing injury risk.

Discussion

The findings of this study underscore the growing potential of machine learning (ML) in injury prediction for professional soccer, allowing for an enhanced understanding of risk factors and more effective injury mitigation strategies. Our results confirm that workload-related variables, particularly

high-speed running, sprint frequency, and decelerations, play a crucial role in predicting non-contact injuries.

Interpretation of Model Performance

The study employed two evaluation strategies—cross-validation and a train/test split approach—providing a comprehensive assessment of model performance. The cross-validation technique enabled a robust performance evaluation across different data subsets, ensuring that all available data contributed to model training. However, it posed a risk of data leakage, as future injury data could unintentionally influence model training. The train/test split approach, which used a temporal constraint to prevent information leakage, addressed this issue by ensuring that all test data occurred chronologically after training data. This method better simulates real-world conditions, where injury predictions are made without knowledge of future events.

Results indicated that the train/test split approach, while more applicable to real-world scenarios, suffered from performance limitations due to the small number of injuries in the test set. Despite this, the approach provided valuable insights into how models generalize over time. The ACWR + EL/IL ratio model (AUC = 0.62) consistently outperformed models relying solely on ACWR (AUC = 0.57) or EL/IL alone (AUC = 0.59), highlighting the importance of combining multiple workload indicators for improved predictive performance. Alternative models incorporating additional feature interactions, such as Model A (AUC = 0.81) and Model B (AUC = 0.77), demonstrated superior predictive capability, suggesting that more complex ML architectures may be necessary for optimizing injury forecasting. These findings reinforce the need for ongoing refinement of injury prediction models, particularly in relation to feature selection, model calibration, and dataset expansion to improve generalizability and real-world applicability.

Feature Importance and SHAP Interpretability

To enhance model interpretability, SHAP (Shapley Additive Explanations) analysis was employed. This provided valuable insights into how individual features contributed to injury predictions, revealing that workload spikes, maximum speed variations, and sudden decelerations played the most significant roles in identifying injury-prone athletes.

- **Max Speed (EL/IL & ACWR features):** High-intensity sprinting sessions were among the most predictive factors for injury occurrence. Players who exhibited sudden increases in maximum sprinting speed, particularly in conjunction with spikes in workload metrics such as ACWR and EL/IL ratios, showed a higher probability of sustaining non-contact injuries.

The relationship between max speed and injury risk is likely due to the increased mechanical and neuromuscular demands associated with high-speed running, which can lead to muscle fatigue, microtrauma, and reduced neuromuscular control. This aligns with previous research indicating that abrupt increases in sprinting intensity may exceed the adaptive capacity of muscle tissues, particularly in hamstrings and quadriceps, making them more susceptible to strain injuries. In practical terms, monitoring max speed trends and integrating progressive sprint exposure into training regimens could be essential in mitigating injury risk in elite soccer players.

- Number of Sprints (>19.8 km/h per minute): The frequency of high-speed bursts showed a strong association with injury occurrence, reinforcing previous research linking sprint exposure to increased muscle strain and neuromuscular fatigue.
- Decelerations (-3 m/s², ACWR adjusted): Sudden stopping and cutting movements created eccentric loading forces, increasing injury risk, particularly for players who experienced previous injuries.

The SHAP analysis confirmed that these workload-related metrics were the most significant contributors to injury prediction. The model highlighted that abrupt increases in max speed, sprint frequency, and deceleration intensity were closely linked to injury occurrences, reinforcing the notion that sudden workload fluctuations pose a major risk to player health.

Furthermore, the SHAP analysis provided individualized risk assessments, demonstrating that different players had varying thresholds for tolerating high-intensity efforts. This suggests that player-specific workload management strategies should be prioritized, rather than adopting a uniform approach to injury prevention.

Another key takeaway from the SHAP results was the interplay between prior injury history and workload spikes. Players with a previous injury were significantly more susceptible to reinjury when exposed to high sprint volumes or excessive decelerations within a short time frame. This aligns with existing research emphasizing the need for gradual reintroduction to full training loads post-injury.

Overall, SHAP provided essential interpretability to the model, ensuring that injury risk predictions were not treated as black-box outputs but were instead grounded in identifiable and actionable biomechanical factors. These insights can guide practitioners in modulating training intensity, implementing individualized injury mitigation strategies, and refining return-to-play protocols for previously injured athletes.

Practical Implications for Injury Prevention

The insights derived from this study offer several practical applications for injury prevention in elite soccer:

1. Optimizing high-speed running and sprinting loads: Since sprinting frequency and high-intensity decelerations emerged as key predictors of injury, monitoring and modifying these parameters during training could help reduce excessive loading.
2. Managing workload fluctuations: the predictive value of ACWR and EL/IL ratios emphasizes the need to monitor sudden changes in training loads to prevent injury risks. Large spikes in acute workload relative to chronic exposure can exceed an athlete's adaptive capacity, leading to fatigue accumulation and increased susceptibility to non-contact injuries. Similarly, a mismatch between external workload (e.g., sprinting distance, acceleration loads) and internal physiological responses (e.g., heart rate variability, perceived exertion) may indicate a heightened injury risk.
3. Implementing individualized recovery protocols: Given that previous injury was a strong predictor, designing personalized rehabilitation and workload adaptation programs based on ML-driven risk assessment can help mitigate recurrence risks.
4. Integrating ML-based injury monitoring into coaching strategies: The ability of ML models to provide real-time injury risk assessments could aid practitioners in making informed decisions about workload management and training periodization. ...

Limitations and Future Directions

Despite promising results, several challenges remain in implementing ML-driven injury prediction models in professional soccer:

- Data Imbalance: The dataset contained only 25 recorded injuries, which could affect the model's ability to generalize. Future research should explore strategies such as data augmentation, transfer learning, or increased injury tracking across multiple seasons.
- Variability in Model Performance: While the ML models demonstrated promising predictive capabilities, their performance was not uniform across all injury cases. Certain models, particularly those incorporating ACWR and EL/IL ratios, showed improved accuracy in predicting injuries associated with workload spikes. However, alternative models (e.g., Model

A and Model B) performed better overall, highlighting the potential benefits of more complex architectures and feature interactions.

- Differences in model generalization were observed when comparing cross-validation and temporally constrained train/test split approaches. Cross-validation consistently produced high AUC values due to its comprehensive dataset utilization. However, the train/test split approach, while more reflective of real-world scenarios, highlighted performance inconsistencies when predicting injuries later in the dataset. This suggests that injury risk factors evolve over time, requiring adaptive modelling techniques such as longitudinal tracking and recurrent neural networks (RNNs) to enhance predictive stability.
- Additionally, variability in model performance may stem from heterogeneous injury mechanisms. While high-speed running and sprinting frequency were key predictors of hamstring injuries, other non-contact injuries (e.g., knee or ankle sprains) may be influenced by biomechanical and neuromuscular factors not fully captured in our workload-based approach. Future models should explore injury-type-specific predictors, incorporating movement asymmetries, joint loads, and neuromuscular control markers.
- To mitigate inconsistencies, advanced feature engineering techniques such as interaction terms, polynomial features, and domain-adapted feature selection should be explored. Moreover, incorporating explainable AI techniques (e.g., SHAP, LIME) can enhance model transparency, fostering greater trust and usability in professional soccer environments. Future iterations of ML-based injury prediction models should aim to balance model complexity, interpretability, and real-world applicability to ensure effective decision-support systems for sports scientists, coaches, and medical staff.
- Feature Selection Complexity: Although feature importance analysis helped identify key predictors, the interaction effects between multiple workload variables still require further investigation. Future models should explore nonlinear relationships and multi-dimensional interactions using more advanced ML techniques such as deep learning.
- Limited External Validation: To enhance generalizability, the model should be tested on different teams, leagues, and playing levels.

Future research should aim to:

- Incorporate real-time biomechanical and physiological markers to provide a more holistic view of injury risk.
- Develop hybrid ML-Human decision-support systems, integrating AI-driven risk assessments with domain expertise from sports scientists and medical professionals.
- Improve model explainability and user-friendliness, ensuring ML-driven tools can be effectively used by coaching staff in real-world settings.

Conclusion

This study demonstrates that machine learning-based injury prediction models can provide valuable insights into non-contact injury risk factors in elite soccer. By leveraging key workload indicators, including max speed, sprint frequency, and decelerations, and incorporating ACWR and EL/IL ratios, the models effectively identified injury-prone athletes. The integration of explainable AI techniques such as SHAP analysis further improved model interpretability, allowing for player-specific workload assessments and individualized risk profiling.

While the study highlights the effectiveness of ML-driven injury prediction, it also emphasizes the importance of contextualizing workload fluctuations and recovery strategies. Injury risk is inherently multifactorial, and while workload metrics serve as strong predictors, additional factors such as neuromuscular fatigue, biomechanics, and player-specific recovery profiles must be considered to improve prediction accuracy and reduce false positives.

From an applied perspective, these findings reinforce the need for real-time monitoring systems that combine ML insights with expert human decision-making. Future research should focus on expanding injury prediction models by integrating biomechanical markers, physiological adaptations, and individualized workload trends to create adaptive, player-specific risk assessments.

By leveraging ML-driven approaches, professional clubs can enhance injury risk monitoring, optimize training loads, and improve player longevity. The study contributes to advancing injury prevention strategies by providing an interpretable, data-driven, and actionable ML framework that can be seamlessly integrated into elite soccer environments.

3.7 A New Conceptual Framework for Managing Hamstring Injury Risk in Soccer – Implementing a Data-Informed Approach: A Brief Review –

Guglielmo Pillitteri, Filipe Manuel Clemente, Marco Petrucci, Hugo Sarmiento, Antonio Figueiredo, Tindaro Bongiovanni, Antonino Bianco, Giuseppe Battaglia, Tim J. Gabbett - Biology of Sports

1. INTRODUCTION

Despite significant efforts from the scientific community, sporting injuries, particularly hamstring injuries, have increased in the last two decades (115, 485). This inevitably, and justifiably, results in the questioning of the efficacy of contemporary injury prevention and rehabilitation strategies. Accordingly, it is important that the scientific community critically assesses its approaches in this area. Within the literature, various factors have been associated or related with injury (5, 130, 132, 216, 218, 227, 490, 491). Typically, these research approaches have commonly centered upon singular risk factors, with a large quantity of research focusing specifically on training load (TL)(492). Here, there is a risk that the lens adopted is too narrow, and too much emphasis has been placed on too few variables, such as singular training load metrics, as ‘the cause’ of injury (14). This has likely contributed to incomplete understandings of injury prevention that fails to appropriately capture its multifactorial nature (5, 80, 130, 131).

Although several factors are related to injury (4), clear cause-effect relationships between many of these factors and injury occurrence has not been established (132, 221, 493, 494). A relevant contribution highlighting a lack of causal understanding in athletic injury research has been offered by Kalkhoven (2024), who outlined the general absence and lack of utilisation of appropriate causal inference structures and tools (such as frameworks, models and causal directed acyclic graphs (DAGs)) to guide causal inferences within athletic injury research (494). Despite these limitations, and while not necessarily reflective of causation, there have been many studies that have investigated the relationship between injuries and TL, finding an association between high EL, such as HSR, sprinting and non-contact hamstring injury (79, 266, 495). In the same way, studies have shown that rapid increases in both EL and internal load, based on the Acute Chronic Workload Ratio (ACWR) (496) are associated with injuries even if other fundamental factors such as moderators (i.e. internal characteristics such as strength and aerobic fitness that may increase or decrease injury risk at given workloads) and mediators (i.e. increase the risk of injury as in the example of neuromuscular fatigue)

have not been considered (497). Consequently, care must be taken when applying this information in practice.

Despite these limitations, some studies have provided valuable contributions focusing on specific training-related factors which could play an important role in optimizing TL (253) and managing injury (73, 216, 231, 497). Indeed, the large amount of data collected by electronic performance and tracking devices such as Global Positioning System (GPS) technology has assisted decision-making using a data-informed approach, which also has included attempts to predict injury through machine learning (ML) approaches (10).

For example, Rossi and colleagues (106) predicted injuries in soccer players via a multi-dimensional analysis in which only GPS (i.e., EL) measurements were considered, while Vallance et al (23), used both internal and EL to predict injury. While promising results could be offered by prediction studies in the future, Bullock et al., have strongly questioned the quality of existing prediction models, reporting that 98% of sport musculoskeletal injury prediction models (and 79% of studies) were rated as high risk of bias (498). This may potentially explain the large amount of conflicting results within the literature pertaining to the relationships between TL and injury (89, 132, 221, 494). Indeed, Jasper et al., (21) reported that the evidence relating both external and internal load to injuries is scarce, suggesting that daily monitoring of TL along with the individual player's characteristics allows a better understanding of the relationship between TL, physical fitness, player's condition and injury risk (IR).

In light of this, Gabbett (216) proposed that effective TL management, which entails avoiding TL spikes while simultaneously enhancing chronic load, may improve players' fitness and reduce injury rates. Indeed, in cricket fast bowlers, players who accrued greater chronic loads experienced lower injury risk than players with lower chronic loads (499). Although these findings require further research confirmation, it has been indicated that high-intensity metrics might be most suitable for detecting injury risk in athletes. This is particularly evident for hamstring strain injuries, with HSR and sprinting loads associated with these events (80, 491, 494, 500).

Although studies to date have contributed to the understanding of training load-injury relationships in various contexts (14), unfortunately, no study satisfies the criteria for establishing an appropriate cause-effect relationship. Indeed, randomized controlled trials (RCT) investigating the TL and injury relationship are scarce (494, 501). Furthermore, the majority of studies in this area are retrospective investigations and observational, which are particularly susceptible to various forms of bias, such as confounding (i.e., occurs when a third variable, known as a confounder, affects both the independent variable [the cause or treatment being studied] and the dependent variable [the outcome or effect being measured] (494), leading to a spurious [non-causal] associations between variables.

Accordingly, until appropriate causal inference tools, processes and methods are developed and adopted, which is a complex undertaking due to the multifactorial nature of injury, it is possible to only detect associations or make predictions from such data, and claims of causation should be avoided (Kalkhoven 2024) (106, 220, 494). This emphasises the lack of an identified cause-effect relation between the factors analysed and the onset of injuries (132, 494).

In practical settings, due to the complex nature of athletic injuries, when a single factor, such as training load, is attributed as the exclusive cause to the occurrence of an injury, a cognitive bias may drive reasoning at the expense of more logical approaches based on accurate knowledge of the underlying injury mechanisms. These risks misunderstanding the “real” role of TL in the injury causation and injury reduction process (5, 80, 490, 494), leading to poor training load management strategies. Instead, a more logical approach might be to understand the “weight” of each risk factor implicated in the onset of injuries and how these risk factors are interconnected (490), thereby avoiding rash judgments and poor decision-making based on cognitive biases (494, 502). To avoid these issues, it is important to properly conceptualise the problem of athletic injury occurrence through the utilisation of conceptual frameworks (5, 490, 494). This will assist with both defining the problem of injury occurrence, laying bare any causal assumptions, and understanding the limitations in the measures that underpin decision-making processes (494).

While Kalkhoven (494) have provided a useful theoretical contribution and in depth understanding relating to the need for implementing causal inference approaches to injury research, suggesting the use of frameworks and appropriate DAGs, Gabbett *et al.* provided a practical framework on training monitoring and athlete management (2, 227, 497). These authors suggested that a combination of EL, internal load, perceptual well-being, and readiness to train/compete data delivers more meaningful individual training prescriptions compared to data (data-driven approach) derived from any single athlete monitoring tool, ultimately leading to a more holistic injury prevention strategy (2).

Based on the previous consideration, two concepts should be kept in mind. The first concerns the awareness that although TL may be implicated in injury occurrences (5, 80, 494), current measures may not be sensitive enough to provide precise or reliable predictions of injury risk necessary to justify a data-driven approach to managing athletic injury risk management using this data. No study has ever demonstrated, with the appropriate methods, a causal attribution of TL on injury (494), while the emphasis on a single factor for predicting athlete injuries (TL and any EL variables such as sprinting included) is likely too reductionist to yield reliable predictions. The second concerns the on-field practice of training load management, which is the main factor that sports scientists can influence on a day-to-day basis. In this context, a data-informed approach that is carefully integrated

with the goals of the athlete and the organisation is recommended to optimize training prescription (e.g. optimal adaptation, enhance physical performance, and potentially prevent injury). This will help minimise potential conflicts among relevant stakeholders e.g., athletes, staff, organisation etc. regarding inappropriate restrictions of training load that overreach in their interference with training processes. In this approach, using training load to manage injury should be secondary to, and should not undermine in a conflict-inducing manner, the performance goals of the athlete or organisation (503) (362, 504). Accordingly, when decisions are made in relation to restricting training load, a holistic approach should be adopted where such decisions are not made using an isolated data-driven approach i.e, by training load data alone, but should be carefully weighed against the training and performance requirements of the athlete and organisation.

Since confusion, misinterpretations and cognitive bias may still be present in the real-world, as highlighted by the small effect of injury prevention strategies (485), our conceptual framework will explore injuries that occur in soccer, focusing on the main role of TL. Hence, the aims of this paper are 1) summarize the main findings on non-contact injury in soccer reporting the most important risk factors for hamstring injuries, including the relationship between TL and injury; 2) describe a conceptual framework of soccer injuries, highlighting a possible cognitive bias when practitioners attribute a single cause, such as training load, to injuries. Finally, we present a qualitative approach through a new conceptual framework on non-contact soccer injuries by including an example from high performance sport where a data-informed approach is used to support non-contact hamstring injury prevention strategies.

To achieve our objectives, this article is structured as follows: Section two delves into the prevalent incidence of injuries in soccer, specifically hamstring strains, elucidating advances in causal understanding and emphasising the critical need for accurate injury reporting and robust prevention strategies. It highlights the complex biomechanics of hamstring function during activities like HSR and sprinting. Section three explores cognitive biases as it relates to injury and training load, stressing the importance of recognizing injuries' multifactorial nature and the pitfalls of oversimplified causal explanations. Section four critically reviews conceptual frameworks on sports injuries, emphasizing their multifaceted origins and cautioning against attributing injuries solely to TL. Section five examines conceptual frameworks on training load and injury in soccer, emphasizing the intricate interplay between workload and injury risk. It describes the necessity of optimizing performance while minimizing injury risk through balanced training intensity and duration. Finally, section six introduces a data-informed approach to load management in soccer, demonstrating how integrating the monitoring of external and internal loads with applied physiology and training methodology can

support training prescriptions, and careful consideration should be taken when implementing load managements to reduce injury risk when it is in conflict with the training and performance goals of the athlete.

2. WHAT ABOUT NON-CONTACT INJURIES IN SOCCER?

In soccer, hamstring injuries are prevalent and costly, impacting both player health and club finances. Epidemiological studies indicate high injury rates, particularly during matches and among professional male players. The focus on hamstring injuries centres on their biomechanical causes during HSR and sprinting, where the muscle's role as an eccentric brake is crucial in decelerating knee extension. Despite differing theories on the exact injury mechanisms—whether during late swing or early stance phases—research underscores the need for targeted prevention strategies. Factors like insufficient eccentric strength and inadequate exposure to HSR during training contribute significantly to injury risk, necessitating precise training-to-match ratios and tailored exercises to enhance muscle capacity and mitigate injuries. Understanding these biomechanical complexities not only informs injury prevention but also underscores the complex interplay between TL, muscle function, and injury occurrence in soccer.

In 2006, Fuller et al. published a consensus statement (113) addressing soccer injuries. This was prompted by the variety of definitions and methodologies employed in studies, resulting in conflicting results, confusion, and challenges in comparing studies. In an updated version (114), the authors provided recommendations on how injury incidences should be reported to mitigate methodological discrepancies when comparing studies (113). For example, the authors suggested accurately reporting definitions of injury, recurrent injury, severity, training and match exposures, location, type, diagnosis, and causation (114).

Soccer injuries have been extensively studied, as they have significant negative repercussions on the health of players and the financial burden of clubs (115, 116). Indeed, the mean cost of an injured player on a professional team has been reported to be 500.000€/month (128). Epidemiological studies have reported that soccer results in high injury incidences at the professional, amateur, and youth levels (117-120). Overall, the incidence of injuries in male professional soccer players is 8.1 injuries/1,000 hours of exposure (121). At both the professional and amateur levels, the incidence of injuries is higher in matches than in training sessions, with the lower extremities having the highest incidence rates (121, 122).

Specifically, hamstring strain injury (HSI) is the most prevalent non-contact injury reported in professional male soccer (12–14% of all injuries (115)), accounting for 37% of all muscle injuries

sustained (116, 123). Furthermore, the reinjury rate of HSIs ranges from 16–60% (123). In contrast, anterior cruciate ligament (ACL) injuries are considered among the most severe, with a time loss of 185–256 days per injury. Ekstrand et al. (2011) (118) reported that players can have a mean of 14 competition days lost per injury (range: 1–128 days for muscle injuries), severely harming team performance and creating a financial burden (127) on the players and their clubs (127).

2.1 KNOWLEDGE ABOUT HAMSTRING INJURY AETIOLOGY

The high incidence of injuries can be attributed to numerous factors (multifactorial aetiology (129-131)), including the high intensity of play, which has increased over the years, and the large number of matches played during the season. Given the negative impacts of injuries on sports teams, there is a pressing need to enhance the assessment and multi-analysis capabilities to pinpoint the primary factors associated with injuries. This will aid practitioners in identifying strategies to mitigate injury risk through interventions and data-informed practices.

Although several studies have focused on identifying the main risk factors of hamstring injuries (505-507) and implementing effective prevention and rehabilitation strategies (508-511), a consensus on hamstring injury mechanisms has never been established. Two main hamstring injury mechanisms related to running have been reported in the literature (512). The first is that a hamstring injury is more likely when experiencing the highest load during active lengthening (simultaneous hip flexion and knee extension) observed in the late swing phase (commences as the hip reaches peak flexion [approximately 100°] and then starts to extend in preparation for foot strike)(512) of the running gait cycle (513, 514). Conversely, Mann et al. (515) considered that the primary injury mechanism is the initial stance phase (begins at foot strike, where the hip extends while the knee flexes) (512) because it involves large forces working in opposing directions as the body is pushed forward over the touchdown point.

Although most studies on hamstring injury during running have reported high rates of injuries during the late swing phase (516, 517), the stance phase has been also considered critical for this kind of injury due to considerable eccentric loading. Certainly, the biceps femoris long head (BF_{lh}) shows greater force during the stance phase, while the semitendinosus (ST) shows greater force than the BF_{lh} during the swing phase. As the BF_{lh} is more susceptible to injury during running than the ST, hamstring injuries are more likely during the stance phase (518) while several studies have reported that hamstring injuries occurs during the late swing phase of sprinting (517, 519-521).

Askling et al. reported that hamstring injuries can occur during either HSR or stretching movements (510). An injury caused by the first type of movement affects the BFLh and shows a lower severity and a shorter recovery time than an injury caused by stretching movements, which commonly involve the semimembranosus (509, 518, 522).

Of note, fatigue reduces hamstring eccentric strength, thereby increasing the risk of injury (523, 524), and reinjury is associated with lower hamstring strength endurance (525). Given the relevant biomechanical implications of HSR activities on hamstring injuries (526), studies have implemented prevention and rehabilitation strategies targeting these activities. One study carried out by Aiello et al. (527) reported that 16 of 17 hamstring injuries occurred when the players were accelerating to or decelerating from a speed of >25 km/h (i.e. HSR, very HSR, or sprinting) (528). Specifically, players were running for (median and interquartile range) 16.75 m (8.42–26.65 m) and achieved a peak speed of 29.28 km/h (26.61–31.13 km/h), which corresponded to 87.55% of players' maximal speed (78.5–89.75%). Moreover, injuries occurred whilst players were in a position of hip flexion and knee extension (i.e., late swing phase) experiencing high eccentric hamstring loading, in accordance with previous studies (529).

Given the effect of HSR on non-contact injuries (67) periodized exposure to both HSR and sprinting within the microcycle of a soccer season could help players tolerate the demands of competition, while minimizing injury risk. Accordingly, practitioners should seek an optimal training-to-match HSR ratio even though high variability exists due to different training methodologies among teams. For example, Clemente et al. (267) analysed the training-match ratio (calculated based on total distance, player load and total number of high ($> 3 \text{ m}\cdot\text{s}^{-2}$) accelerations and decelerations) and found that, on average, training sessions represent 1.8 times the effort expended in a single match. However, this figure can vary (ranging from 0.6 to 1.8) significantly depending on the player's position and the number of training sessions per week (6, 268).

The underexposure of players to HSR during training may significantly impact their ability to adapt to the demands of a match. Buchheit et al. (491), have suggested an association between accumulated HSR and sprinting distance during the training days over the microcycle and match injury occurrence. The authors (491) found no match hamstring injuries when players were exposed to running bouts at > 90% maximal sprinting speed (i.e. a five-day microcycle) and > 95% maximal sprinting speed (i.e. three-, five- and six-day microcycles) during training sessions leading into matches. However, injuries still occurred during 85% of the microcycle when there were no or low volumes of high-velocity speed exposures (> 85 or $> 90\%$). These results suggest the paramount role of peak speed in adapting the hamstring muscles to withstand match demands. A contribution on this topic has been offered by Buchheit (7, 79, 266), concerning the training microcycle programming

based on scientific evidence aiming to “informing” the experts to support make decisions. Specifically, author explored the management of post-match recovery and compensation training, suggesting post-match (MD+1) the need compensation for high intensity and sprint training (at MD+1) to maintain the performance of substitutes and reduce the risk of injury (1, 7, 244). A paramount factor concerns the high-speed peaks, as a strategy to reduce the risk of injury. Indeed, the importance of training at near-maximum speed ($>95\%$) in MD-2 may be associated with a reduction in injury rates (79, 266).

Physiological aspects related to soccer players and the references values derived from match-demand knowledge should be considered when training program design is required. For examples, professional player cover total distances ranging between 10-13 km of which around 900 m and 250-300 m travelled at HSR (speed ranging from $19.8 \text{ km}\cdot\text{h}^{-1}$ to $25.2 \text{ km}\cdot\text{h}^{-1}$) and sprinting (speed $\geq 25.2 \text{ km}\cdot\text{h}^{-1}$), respectively (37, 58, 59). The importance of HSR and sprinting distance has been recently discussed in a systematic review [34]. Specifically, during official matches, HSR and sprint running distances ranged from 618 to 1,001 m and 153-295 m, respectively, in professional male soccer players. These values should be bearing in mind to optimize soccer training since are strongly implicated in hamstring stress (7, 67, 80, 510). In this way, understanding hamstring functioning during HSR and sprinting considering their implication on hamstring injury could help practitioners to consider appropriate prevention strategies to mitigate injury risk.

2.2 HAMSTRING FUNCTIONING DURING HIGH-SPEED RUNNING AND SPRINTING AND ITS INJURY IMPLICATIONS

In the soccer context, most hamstring injuries occur when players are sprinting at above 80% of maximum speed (527), highlighting the strong relationship between high-intensity running and hamstring loading. Published evidence (80) indicates that hamstring muscles function as an eccentric energy-absorbing brake that decelerates knee extension and tolerates high mechanical loads in the late swing phase of sprinting. Although hamstring injury has been related to both late swing and early stance/initial contact phases (520, 530), studies have focused primarily on hamstring functioning during the late swing phase of sprinting (517, 519-521).

New theories (i.e. spring-like hamstring phenomenon) proposed by Van Hooren and Bosch (531, 532) on hamstring functioning during sprints involving the eccentric lengthening of the hamstring muscles in the late swing phase (531, 532) have been questioned. Kalkhoven et al. (80) have provided a detailed conceptual exploration of hamstring muscle–tendon functioning during the late swing phase of sprinting. To understand the complex hamstring functioning during sprinting, Kalkhoven et al. [11] comprehensively examined different models of myotendinous unit (MTU) functioning during locomotion (80).

Two main models of MTU functioning during locomotion have been reported in the literature – an efficiency model and a power model –(533, 534). The efficiency model relates to spring-driven MTU behaviour by which muscles act mainly as mechanical struts and perform minimal work while the tendons work by storing and releasing elastic energy to improve locomotor efficiency (533). Conversely, the motor-driven power model of MTU functioning considers muscle actuators and active muscle work as a process by which muscle fibres usually experience large excursions, especially during high-intensity circumstances, with the muscle fibres shortening to produce power (533).

The spring-driven model saves metabolic energy during sprints, as the muscle (contractile element) works isometrically while the tendon performs all the mechanical work. However, some questions have been raised in the literature. Studies have found no difference in the metabolic cost of force production between muscular stretch–shortening cycles (during which the muscle lengthens while active) and isometric contractions (535). Moreover, even though the motor-driven system is predominantly active during high-intensity actions, tendons act as transmitters of muscle contractile force to the origin-insertion points for the generation of limb movements instead of storing and releasing elastic energy (534).

Spring-driven and motor-driven models are not exclusive and can be used according to the task demands, highlighting that muscles act eccentrically under both conditions (536), requiring force production, energy absorption, or the utilization of the stretch–shortening cycle.

Accordingly, the isometric theory should be considered with caution. It should be kept in mind that hamstring muscles adopt a model of functioning including both muscle actuators and active muscle lengthening. Moreover, the amount of eccentric work leading to muscle damage has been related to hamstring injuries during HSR (537).

Conversely, Van Hooren and Bosch's (531, 532) theory indicates that the hamstring muscles passively lengthen during the initial and mid-swing phases of sprinting due to muscle slack during the delay between the start of contractile element activation and series elastic element recoil (538). However, the existence of muscle slack has been questioned in electromyographic (EMG) and

electromechanical studies showing that the hamstrings receive electrical signalling throughout the sprint cycle (80, 539). Moreover, regarding large knee joint ranges with changes in the MTU length that occur during sprints (521, 537), it has been hypothesized that the hamstring fascicles would be required to actively (eccentrically) lengthen and shorten to complete the sprint cycle.

Considering the kinematic and kinetic perspective of hamstring function during the swing phase of sprinting, studies have reported that being biarticular (except for biceps femoris short head), hamstring muscles are stretched during the mid-swing phase as the hip is in a flexed position while the knee is extending (517). Near the end of the mid-swing phase, an exceptionally high peak knee joint extension velocity ($> 1000^\circ/\text{s}$) has been reported with a consequent rapid deceleration of the knee joint. This has been seen with EMG data leading to the active braking role of the hamstrings, especially in the late swing phase, during which they are stretched to maximum or near-maximum length (517). As the eccentric role of the hamstring has been widely established, Kalkhoven et al. (80) made valuable recommendations for hamstring-specific training and injury prevention exercise selection.

Researchers claim that the adaptation derived from eccentric hamstring training may reduce the risk of hamstring injury during sprinting activities (486). Of note, muscle functioning during sprints is derived from the complex interaction between musculoskeletal kinematics and kinetics (540), muscle activation patterns, the neuromechanical regulation of tensions and stiffness (541), and loads applied by the environment. Accordingly, exercises activate the hamstring muscles at a maximum of 60% of the maximal activation exhibited during top-speed sprinting (542), leading to the specific mechanical demands influencing hamstring MTU function during sprinting (such as specific timings and combinations of hip and knee joint angles, velocities, accelerations and moments, magnitude and rates of muscle loading, required combinations of muscle and tendon lengths and length changes, muscle and tendon stretching and shortening velocities and accelerations) (80). Readers should read the work of Kalkhoven et al. to delve deeper into the MTU functioning mentioned above.

In summary, the behaviour of the MTU of the hamstring during sprinting is highly specific and finely regulated for this activity. Selecting hamstring exercises in isolation to replicate hamstring functioning during sprinting is questionable despite the adaptive benefits derived from eccentric exercises specific for the hamstrings for athletes called upon to sprint (80). Therefore, to reduce hamstring injury risk during sprints, practitioners should administer sprint training to enhance the hamstring loading capacity (491). Understanding the key physiological and biomechanical characteristics underlying hamstring function has shed light on the role of sprinting and HSR management. However, despite the implication of a single factors related to TL such as sprinting, the

exclusive causal attribution of load to injury occurrence can be considered a cognitive bias, as we will explore in the next section by following a “psychosociological” perspective.

3. COGNITIVE BIAS BEHIND THE EXCLUSIVE CAUSAL ATTRIBUTION OF LOAD ON INJURY OCCURRENCE: CAN THE CAUSAL-EFFECT APPROACH EXPLAIN THE ACUTE INJURY EVENT?

Several factors, including TL, have been investigated in the literature (5, 14, 21, 132) to fully understand the causal reasons for acute injuries. In the soccer context, practitioners have investigated causal factors that may lead to a non-contact injury, even though the multifactorial aetiology has been widely approved by the scientific community (130-132). Put simply, injuries happen during high-stress situations, such as intensified phase of both official matches and training due to high physical stress and mechanical force that the tissue cannot support (5, 80). The stress and strain experienced by a particular tissue are determined by the interaction between the force applied to a specific tissue and the mechanical properties of that tissue (5).

Accordingly, the inappropriate “load” administered to a predisposed (i.e. not adapted or weak) player seems highly involved in the occurrence of acute injury (5, 227, 497). Although a correlation between TL and injury has been found (14), causation has never been confirmed highlighting the lack of appropriate study design and methodologies (such as a gold standard as RCT). Indeed, causation requires an association between two variables, but association does not necessarily imply causation (494). An association between two factors can occur both with and without a causal relationship. Accordingly, it seems inappropriate and illogical to attribute the cause of a given injury to a single factor related exclusively to work load. In the study of systemic pathologies, such as cardiovascular (543), finding the main risk factors may help reduce the onset and incidence of illness. For further knowledge on the need for causal inference on injury, we refer readers to Kalkhoven (494). Author have highlighted the unfeasibility of RTC in elite real soccer context, suggesting potential strategies that can assist with developing causal understandings of athletic injury such as formation and utilisation of frameworks, models and causal DAGs to overcome the “obstacles” and provide value for research pursuits (494).

While Kalkhoven refers to a high scientific perspective providing useful solution to understand the causative knowledge, a “sociopsychological” perspective leads to the study of injuries should start with logical reasoning (i.e. high cognitive process) considering the possible factors that interact to

determine the onset of injury. For example, a spike in TL could cause an injury in weak players as reported by Windt and Gabbett (227). Unfortunately, the study of higher cognitive processes such as thinking, reasoning, decision-making, and social cognition has been related to bias, error, and irrationality. Authors (502) have reported that bad thinking (i.e. illogical reasoning, trivial decision-making, prejudice and stereotyping) affects people in different contexts. In this way, a cognitive bias, defined as a systematic (not random) error could be the result of a misunderstanding or wrong reasoning when a single factor (including TL and its indicators such as sprinting or HSR) is attributed as the exclusive cause of an injury (5, 132).

Psychologists have reported that people's evaluations of logical arguments are biased by whether they believe the conclusions (502, 544). Moreover, previous knowledge and beliefs influence human reasoning, and only a strong effort of conscious deliberative reasoning can overcome this (502). In the injury field, practitioners have tried to predict injury (output) starting from input variables such as TL indicators. Even though cognitive bias can result from the attribution of "load" as exclusive injury causation, recognizing which indicator is most involved in the onset of injuries would be useful for decision-making in terms of modulating the TL to "reduce the risk of injury". Decision-making can be considered as a mental simulation that requires the assessment of probability and uncertainty. When a deviation from the probability theory occurs, it is possible to consider a fundamental paradigm known as "heuristics and biases." (545).

Biases are observed behaviours, while heuristics (i.e. a short-cut technique for solving problems that would otherwise be intractable given our cognition processing capacity) are theoretical constructs, including availability (546) and representativeness (546). *Availability* refers to someone who tries to estimate the likelihood or frequency of some event by calling to mind examples of the event. The easier it is possible to generate such examples, the more frequent people judge the event to be, even if it can easily be biased. For example, the media or some professionals may attribute injuries exclusively to excessive TL. *Representativeness* heuristic is applied when judging the probability of a sample based on a hypothesis related to similarity. For example, people estimate the probability of an event based on how similar it is to a known situation and compare it to a situation, prototype, or stereotype they already have in mind. Cognitive biases, such as the causative explanation of non-contact injuries, can be related to a framework called dual-process or dual-system theories corresponding with the broad distinction between intuitive (System 1) and deliberative (System 2) thinking.

Based on a revised version of this theory carried out by Evans (502), cognitive biases are not exclusive to heuristic processes but can arise from analytic processing as well. However, within the

theoretical framework, three main principles have been reported. The first one concerns System 2 (analytic), which states that when people think hypothetically, they consider only one possibility or mental model at a time. People focus on only one explicit option when engaged in decision-making (547) and may seldom consider alternatives. This principle could explain the cognitive bias that explains why practitioners often consider one singular factor at a time, such as a TL indicator (e.g. HSR) when trying to understand the cause of an injury.

The second principle asserts that given the current goals of the reasoner, mental models are generated by heuristic or pragmatic processes that are designed to maximize relevance in a particular context. Thus, when people consider a risky prospect, they will normally focus on the most likely outcome first. Similarly, professionals often consider physical exertion (TL) as “the most relevant factor in the field context” as an exclusive cause of injury (548).

The last principle (i.e. the satisficing principle) claims that people’s hypothetical thinking when evaluated by an analytic system is accepted unless there is good reason to reject, modify, or replace it. Of note, cognitive biases arise not only in heuristic systems but also in analytic processing. Stanovich (549) described the tendency to contextualize all problems in light of prior knowledge and beliefs leading to cognitive biases, such as belief bias.

Accordingly, Evans framework (544) refers to the cognitive bias underlying the hypothetical reasoning according to which a single factor such as TL can exclusively cause injury. Indeed, the author pointed out that the *fundamental heuristic bias* (in System 1), is essentially the influence of linguistic and attentional factors, as well as contextualization effects. Essentially, people tend to focus selectively on information that is preconsciously cued as “relevant” per the relevance principle. Similarly, a cognitive bias concerns focalism (550), which is the tendency to place too much emphasis on a single factor or piece of information when making judgments or predictions.

The second bias refers to System 2 and it is called the *fundamental analytic bias*. This bias involves the tendency to accept a current model (hypothesis, possibility) as the basis of inference, decision, or action without sufficient evaluation or consideration of alternatives (singularity and satisficing principles).

Based on the previous considerations, it could be stated that when a practitioner, coach, manager, or the media attributes a single factor as exclusive cause to the onset of non-contact injuries, their reasoning is influenced by cognitive bias. Although it may seem contradictory, stating that TL is not the exclusive cause of an injury does not imply that TL is not strongly implicated in the occurrence of the injury. Indeed, it is logical that injury happens as a consequence of a certain amount

of load where tissue loading exceed tissue strength (551, 552). Indeed, Kalkhoven have explained the mechanism of athletic injury applying DAGs, where two components (i.e., the mechanical loading (force) experienced by a tissue and the mechanical strength of that tissue, “one (or both) of which all causal variables must act through, i.e. these two components are reflective of the proximate (ultimate) mechanism of athletic injury (494). This perspective confirms that TL is not an exclusive cause of injury but is a highly implicated component that interacts with other components ('internal' to the athlete, referring to factors related to muscular tissue). Understanding multifactorial and complex phenomena related to human beings' health requires a high level of knowledge, logical reasoning, evidence-based information, causative inference tools and the elimination of cognitive biases that harm decision-making and the understanding of certain dynamics with related injury reduction strategies. Moreover, qualitative research including a conceptual framework could lead a valuable approach to study the injury aetiology (494). Figure 3.29 shows a conceptual framework related to the impact of cognitive bias on TL-injury causation. In the next section we will present an overview of the main conceptual frameworks on sports injuries which attempt to attribute injury to a single cause.

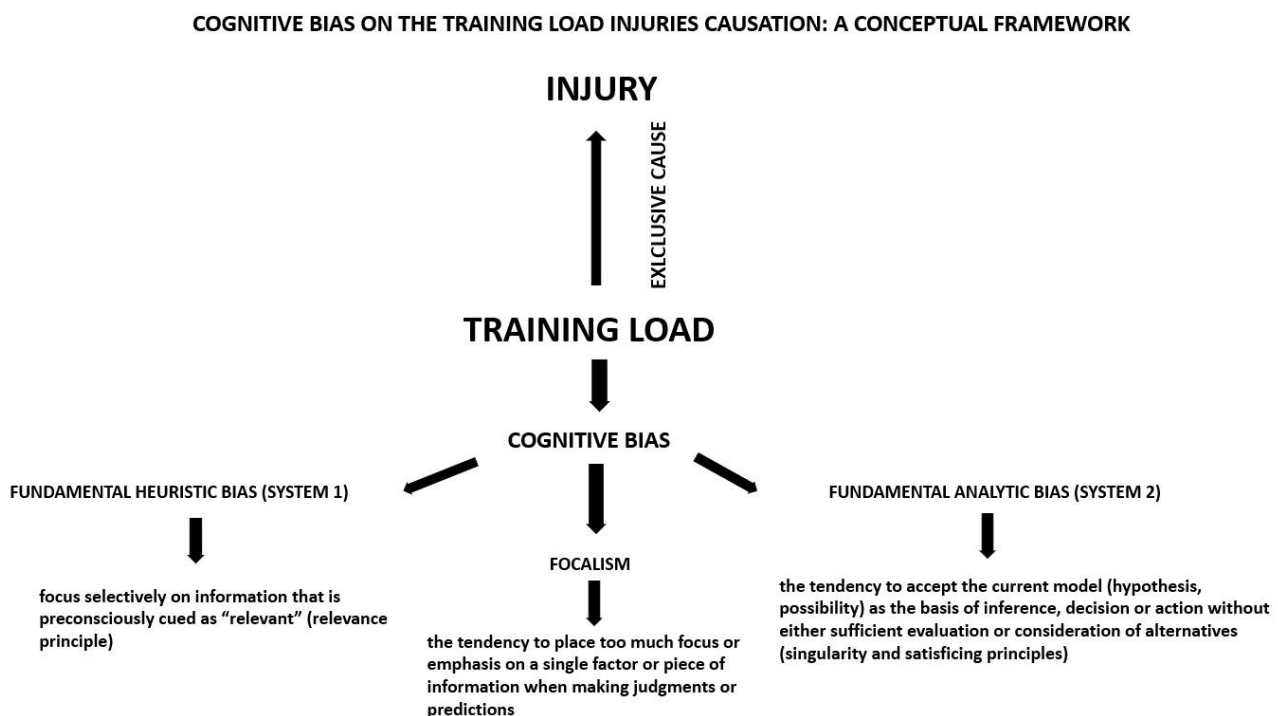


Figure 3.29 Cognitive bias on training load injury causation: a conceptual framework

A conceptual framework related to the impact of cognitive bias on TL-injury causation. Three main cognitive bias (i.e., *Fundamental Heuristic Bias*, *Focalism* and *Fundamental Analytic Bias*) have been considered when TL is attributed as an exclusive cause of injury.

4. CONCEPTUAL FRAMEWORKS ON SPORTS INJURIES: IS IT POSSIBLE TO FIND AN EXCLUSIVE SINGLE “CAUSE” OF INJURY?

The literature reports some frameworks on sports injury to provide useful insights into injury mechanisms and with the attempt to outline appropriate prevention strategies. Kalkhoven's (5, 494) frameworks have made a significant contribution by incorporating a holistic perspective to understand sports injuries. However, the concept of cause-and-effect relationships in injury onset should be approached with caution. To comprehend the cause-and-effect dynamics behind an injury occurrence, practitioners need to address the following questions: Why did a particular athlete sustain an injury at a specific time and under particular circumstances? Is a single factor (such as TL) exclusively responsible for a specific injury?

Building on the information discussed in the previous section, these questions could reveal a cognitive bias, as it is not entirely possible to exclusively attribute a single factor to all occurrences of injuries. Therefore, injuries can be seen as the result of multifactorial human factors. Nonetheless, these authors (5) have conceptualized the complex relationship between relevant potential causal contextual factors, such as physiological and mechanical tissue properties, and the occurrence of injuries, presenting a framework for specific injury mechanisms. Furthermore, the framework introduces the concept of material failure. This concept posits that failure occurs when the strength of a material is surpassed by extreme stress and strain, induced by either the application of a single high-magnitude stress or repeated applications of a load at a certain percentage of the material's ultimate strength (553).

Based on this concept, most contact and non-contact sports injuries occur as a result of exposure to a singular stress or repetitive stresses and strains (216, 553, 554). In this context, *stress* refers to the internal forces experienced by a structure (i.e. force per unit of area), while *strain* is defined as the amount of deformation or length change in the direction of an applied force (555).

From a mechanical standpoint, the literature (80) suggests that the primary "cause" of injury is often linked to exceeding the load tolerance or strength of a tissue due to an applied load. While this mechanical perspective has deepened our understanding of injury mechanisms, our viewpoint challenges this "cause-and-effect" relationship, arguing that the assumption of causality is not proven. While this concept outlines a physiological mechanism of injury, injury prevention necessitates an understanding of why a tissue becomes injured (i.e. why it is not adapted to withstand a given load) under specific circumstances at a particular time. Nonetheless, exploring the interactions between structural load tolerance and the application of load provides a valuable contribution to both research and on-field prevention strategies.

According to Kalkhoven's (5) framework, six causal contextual factors interact with each other, including an individual's physiological profile and functioning, mechanical properties, and the force applied to the body and the various tissues within. Meanwhile, the load tolerance of the structures subject to injury and the load applied have been related to a deeper level of the framework (5). The internal stress and strain experienced by specific tissues have also been included as the structural load tolerance and tissue-specific strength. This refers to the main framework's concept of injury that results if the load applied to a specific structure exceeds the load tolerance.

Based on the perspective provided by the aforementioned framework, the role of tissues (i.e. muscles and tendons) is strongly related to the load experienced by players to implement appropriate injury prevention strategies. In a recent review carried out by Kalkhoven et al. (5), the relationship between TL and injury has been investigated; authors showed how the available TL indicators may relate to the causal pathways of tissue damage and injury incidence. Given the prominent role of mechanical loading (i.e., the forces experienced by specific biological tissues) and a mechanical fatigue failure process that is etiologically relevant to tissue damage, the authors suggest that the quantification of mechanical loading at the tissue-specific level is crucial to understanding the complex aetiology of injury. Accordingly, TL indicators should quantify or reflect mechanical loading, the mechanical load-response pathway, and, consequently, tissue damage and injuries.

As noted by the authors (5), an accurate assessment and quantification of the mechanical load-response requires an invasive laboratory setting, making their application unfeasible in real-world scenarios. The EL indicators that best reflect a mechanical load represent a proxy measure of the force applied to muscle tissue and the related structures responsible for high-intensity actions such as HSR, sprint and intense accelerations and decelerations.

While some authors have criticized this approach (5, 221), arguing that GPS does not offer a reliable proxy measure for the mechanical loads experienced by specific tissues – thereby leading to inconsistent results when associating GPS data with injury – this practice (i.e., data-informed approach) remains one of the main practical solutions available in the field to support applied physiology and training methodology. Although attributing TL as the exclusive cause of injury is a “bias”, it is highly implicated in the mechanism of injury, since it has been widely demonstrated from contribution offered by the literature (80), it must be controlled. In fact, managing TL, focusing on the most implicated factors such as sprint (see previous sections), allows to support the training prescription, reaching an optimal training result (positive adaptation of the athlete/strong athlete) with the consequence of protecting players from the occurrence of injuries.

Nonetheless, this approach represents a possible on-field method for correlating players' internal responses to manage load as a fundamental injury prevention strategy. While mechanical

loading and the mechanical load response pathways are crucial for understanding tissue damage, the psychophysiological load-response pathway, including measures of physiological (e.g. heart rate, lactate concentrations) and psychophysiological stress (e.g. ratings of perceived exertion), should also be considered.

However, authors have pointed out that such internal measures poorly correlate with psychophysiological fatigue indicators (26) and do not accurately reflect the mechanical load experienced, leading to inconsistent associations and causations with injury. Although this perspective seems logical and appropriate, monitoring internal load remains a key strategy for understanding an athlete's response to EL. This is instrumental in determining whether the training schedule is suitable in a given context and can help avoid suboptimal training practices that could lead to injuries.

Kalkhoven et al. (5) reported that understanding the causative role of TL on injury requires establishing, not assuming, the contributions of both mechanical and psychophysiological fatigue to injury aetiology. Practitioners and researchers should exercise caution when attempting to establish a simplistic and exclusive "causality" relationship between a single factor, such as TL, and injury. Instead, a multifactorial interrelation perspective that considers specific circumstances at specific performance times should be adopted to understand potential "causes" of injury. The generalization of an injury cause is challenging, and the interplay among injury risk factors, such as EL and tissue loading response, must be understood from a complex multifactorial perspective.

In this context, a complex systems approach to sports injuries has been advocated by Bittencourt et al. (490), who defined a *complex system* as an entity with parts that interact with each other and which is characterized by inherent non-linearity due to recursive loops and complex interactions among units. Through this approach, practitioners should identify the patterns of relationships among determinants (i.e. specific risk factors related to biomechanics, training characteristics, psychology, and physiology) within a specific context (e.g. soccer or ballet), the regularities (profiles) that concurrently characterize injuries, and the emerging patterns from the complex web of determinants.

According to Philippe and Mansi (556), small changes in a few determinants can lead to large and sometimes unexpected consequences, indicating the non-linear behaviour of determinants interacting with each other. Other authors suggest recognizing the frequent patterns of interaction among multilevel risk factors rather than identifying risk factors at the unit level (557). For example, Mandarino et al., have investigated the interaction between TL markers, modifiable and non-modifiable risk factors, through a machine learning approach, aiming to predicting non-contact injuries in professional young soccer players (425). The data-mining technique applied have showed

that recovery status, internal load markers, modifiable (height, body mass) and non-modifiable factors (maturity status), interacting each other, can modify the predisposition to risk of injuries (425).

Sports injury research should focus on the observable regularities arising from simple and complex interactions among elements of the web of determinants rather than the risk factors themselves. For instance, typical unanticipated environmental events, high frontal plane knee angles, and hip weakness have been identified as key determinants for ACL injuries in basketball (490). These variables, influenced by factors such as fatigue, age, sex, and TL, interact in specific ways to create a risk profile that depends on the context (e.g., soccer vs. dance).

A single risk factor alone cannot be considered exclusively causative of injury. Instead, identifying a risk profile can inform the probability of injury occurrence, as in the case of an ACL injury occurring when a specific pattern of interaction unfolds in the presence of an inciting event. This approach could enhance injury prediction through the use of complex and appropriate analyses, such as machine learning, to identify injury risk patterns based on the interaction between specific risk factors and player characteristics (12, 311). Supervised learning, which investigates observed outcomes by examining patterns of other factors, is intended to indicate which patterns lead to specific outcomes. However, should keep in mind that, to date, the quality of applied machine learning methodologies have been questioned as high risk of bias (498).

These conceptual frameworks prompt us to reflect on whether searching for a singular cause of injuries is appropriate or if a multilevel causation perspective should be considered. Despite could be contradictory, in real-world soccer scenarios, TL plays a crucial role in improving physical performance and, simultaneously, may expose players to injuries if not tailored to the individual. Understanding the role of TL (which cannot be considered as a single exclusive “cause” but is highly implicated in the occurrence of injuries) could encourage practitioners to adopt a holistic perspective, strongly considering the data-informed approach. In the next section, we will provide a summary of the main conceptual framework on TL and injuries aiming to highlight potential pitfalls, bias as well as reporting the most relevant literature contributions (despite lack of causative perspective such as RTC studies).

5. BACKGROUND: CONCEPTUAL FRAMEWORKS ON TRAINING LOAD AND INJURIES IN SOCCER

Gabbett et al. (2014) defined *workloads* as “the cumulative amount of stress placed on an individual from multiple training sessions and games over a period of time” (235). A combination of intensity, frequency and duration allows one to quantify the demand imposed on a player during both training sessions and matches (171). Coaches prescribe training in a way that disrupts homeostasis to reach optimal adaptations (i.e. the supercompensation cycle). Hence, excessive or insufficient loads should be avoided, as they may lead to detraining, maladaptation, or overtraining among athletes (26, 558).

Accordingly, trying to prescribe training with the optimal load is a difficult challenge for coaches. In light of this, Borresen and Lambert reported that “optimizing training first involves quantifying what the athlete is currently doing” (559). Usually, this load quantification is permitted to predict the performance, training plan, periodization and monitoring, thus establishing athlete readiness and stress while avoiding injuries (2). From a logical perspective, injuries are sustained while an athlete performs an activity that determines a workload (both external and internal). Although coaches seek to maximize performance by manipulating the TL, training is necessary to induce positive adaptations by stressing physiological, biomechanical, and metabolic systems. Accordingly, the scientific community should try to understand how the workload is related to injuries and establish whether simply increasing the load increases injury risk. Recently, researchers have provided some practical applications to explain the complex associations between load measures, indicators, indexes, and injuries (21, 23, 27, 211, 216, 220, 223, 235). Worth noting, while several observational studies have been carried out to understand sport’s injuries, we highlight that literature lack of RCTs that are commonly regarded as the ‘gold standard’ for assessing causality (560), as these types of studies allows to eliminate the effects of confounding variables (494, 560). However, conceptual frameworks represent a feasible and appropriate solution to make conceptual distinctions and organise ideas, deconstructing complex phenomena into relevant theories, assumptions, causal link and concepts of interest such as sport’s injuries (494).

The literature on the complex relationship between load and injuries presents some conceptual frameworks (2, 4, 5, 216, 218, 227, 527, 561). Windt and Gabbett (2017) (227) proposed an updated injury aetiology model, including the effects of workload on injury occurrences. The authors modified previous injury aetiology frameworks (129, 130) by adding the effects of training and competition loads on the dynamic nature of injury risk. The multifactorial nature of injuries is well-established in the literature (218).

Meeuwisse (1994) proposed a multifactorial injury model highlighting the intrinsic and extrinsic risk factors which predispose athletes to injuries (131). Some of these intrinsic factors (e.g. age) are non-modifiable, while others (e.g. strength and endurance) are modifiable. Moreover,

extrinsic (external) risk factors (e.g. the playing surface, protective equipment, or opponent behaviour) make athletes susceptible to injury. Lastly, injuries occur when a certain inciting event arises wherein the biomechanical stress of the event exceeds the tolerance of the athlete's tissues (5, 527).

As reported by Windt and Gabbett (2017) (227), this multifactorial model has been improved and modified by Bahr et al. (129) and Meeuwisse (2007) (130). The first model provided a more exhaustive description of the biomechanical factors impacting the inciting event. Meanwhile, Meeuwisse proposed a “dynamic, recursive injury aetiology model” highlighting that training/match participation predisposes athletes to injury but also modifies subsequent risk (130) (i.e. it modifies certain risk factors through physiological adaptations to training stress).

However, as reported in the workload-injury aetiology model, workload-injury investigations have focused on the relationship between absolute workloads and injury. Several studies have reported an increase in injury risk with an increase in absolute workload (223). Nevertheless, an understanding of the role of workload on injury aetiology should be based on the rationale and knowledge of physiology and training methodology while applying appropriate statistical analysis and data interpretation. Furthermore, it would be illogical to think that a low workload may protect athletes from injury risk because the training aims to adapt the athlete to withstand the match demand (i.e. adapt physiological structures to withstand the match demand). In this way, workloads that are too low compared to match-demand reference values are likely to decrease physical performance and may decrease an athlete's fitness and preparedness to cope with the match-demands. This, in turn, could increase injury risk. Epidemiological studies show that injuries are more likely during matches than training (115, 116, 118, 562).

Another factor relevant to injury risk is how the workload is applied. Studies have examined the relationship between the acute: chronic workload ratio (ACWR), which is calculated based on the acute load (generally one week), chronic load (four weeks), and injury risk (220). Although Impellizzeri et al. (241) have suggested some mathematical and conceptual bias, ACWR has been associated with injury risk (220, 493, 496, 501), but it does not predict injury (106). Specifically, when ACWR is high (i.e. when spikes in training load occur), an increased risk of injury has been found in rugby players (563) and professional soccer players (493, 496).

Despite the associations found between TL and injuries, the rationale that high workload determines injuries has been refuted by Gabbett (2016), who developed the training-injury prevention paradox model (216). The author argued that a high workload is necessary to improve physical capacity and reduce injury risk. In particular, the relevance of chronic loading has been identified as a protective effect against injuries, and weekly fluctuations in load should be kept to a minimum

(~10%). Furthermore, to minimize injury risk, the ACWR should be kept within a moderate range (i.e. training load spikes should be avoided), although it is acknowledged that there will be occasions throughout a season where spikes in workload may occur (e.g. during congested playing schedules or intensified training blocks). While being cognisant of injury risk, practitioners are encouraged to manage training load to optimize the development of physical qualities appropriate for the sport.

To better understand the complex and multifactorial relationship between TL, injuries, and performance, Gabbett (2018) (218) explained why some athletes sustain injuries at an ACWR of ≤ 1.5 while others tolerate extremely high both chronic workloads and ACWR (219, 246, 564). These differences can be explained by the moderators of the workload-injury relationship. Specifically, as explained by Windt et al. (2017), “a moderator acts to either increase or decrease injury risk at a given workload” (219, 227). For example, a spike in workload for athletes with inadequately developed physical capacity (e.g. aerobic fitness, speed, repeated-sprint ability and lower body strength (246, 565)) and low chronic training load (564) have been associated with increased injury risk. The author suggested that practitioners should stratify players according to age, training and injury history, and physical qualities (moderators of the workload) rather than focusing solely on the ACWR or a single training load indicator. However, the ACWR has been questioned and criticized, accordingly care should be taken when associated this metric associated with injury (5).

Moreover, internal and external load indicators should be considered in combination with well-being and physical readiness data to understand an athlete’s risk of injury (2, 566, 567). In light of these considerations, it is possible to conclude that injuries are not directly and exclusively caused by workloads (132). Instead, as reported in the updated injury aetiology model carried out by Windt and Gabbett (2017) (227), “training and competition loads contribute to injury risk through exposing athletes to potentially injurious situations, as well as through their positive and negative effects on numerous modifiable internal risk factors”. This risk modification depends on the total and relative workload applied, leading to positive and negative adaptations. Therefore, workloads can affect injury aetiology through exposure, fitness (i.e. positive adaptation) and fatigue (i.e. negative adaptation).

Authors have included the application of workload framework as the primary process by which an athlete is exposed to various external risk factors and potential inciting events (227). From this perspective, TL is “the vehicle whereby an athlete moves from being a predisposed athlete to a susceptible athlete” (227). Accordingly, predisposed athletes become susceptible to injury when exposed to a training or competition load. Positive adaptations to modifiable internal risk factors may help explain the training load-injury prevention paradox (i.e. high chronic load and high fitness levels may protect athletes against injuries).

The frameworks mentioned above and the aetiology model (227) allow us to understand the workload-injury relationship more accurately. In summary, when athletes sustain a spike in training that they are unprepared for (i.e. a high ACWR), a larger degree of negative maladaptation will occur, modifying some internal risk factors and increasing their predisposition to sustain an injury in subsequent physical stimuli. Conversely, positive physiological adaptations created by adequate load management (i.e. accumulating high chronic workloads while avoiding training spikes) decrease injury risk.

The misinterpretation of workload-injury investigations may also be derived from statistical analysis, a poor study design, and an improper rationale behind the causality assumption (221). Given the fundamental role of statistics in the load-injury investigation, researchers should implement a multilevel (mixed) modelling approach. Such an approach is more appropriate for repeated measures (based on the need to quantify workload during a given period) than simple logistic regression models (which assume the same exposure load across individuals).

Multilevel modelling approaches or frailty models (568) can account for correlated outcomes (repeated workload measures among players), including random effects to predict individual athletes' injury risks. Moreover, specific and more advanced statistical analyses, such as machine learning methods, have been employed for injury prediction. Although no single load factor can be exclusively attributed to injury causation (132), verifying which load indicators are most implicated with injuries can help practitioners implement appropriate prevention strategies.

However, several studies have investigated the relationship between workload and injuries in soccer. Jasper (2017) (21) reported scarce evidence regarding the relationship between external and internal load and injury or illness. Given the extreme complexity of these factors (i.e. TL and injuries), the literature shows conflicting results. Nevertheless, every athletic injury occurs while athletes are exposed to training and competition workloads regardless of the interaction of risk factors and inciting biomechanical events with a lack of direct causality (132). Accordingly, despite the lack of direct causality (i.e., TL cannot be considered as exclusive cause of injury) workload management is one of the main factors that should be considered in injury prevention strategies. Moreover, while practitioners are concerned with workload management (including the monitoring process), an optimal training plan may be essential to increase physical performance and reduce injury risk (132). In this section we reported the main frameworks on sports injuries. In the next section we will focus on our new conceptual framework on non-contact injuries and soccer, delving into the possible implications for HSR and sprinting.

5.1 A NEW CONCEPTUAL FRAMEWORK ON NON-CONTACT INJURIES IN SOCCER

Drawing on the significant contributions made by previous injury conceptual frameworks, our new framework incorporates several pillars supporting its structure. Specifically, we have elucidated the primary mechanisms underlying hamstring injuries, emphasizing the critical implication of HSR and sprinting on injury occurrence (see Kalkhoven' framework (494)). While we emphasized the lack of causality when TL is attributed as exclusively "cause" of injury, TL is strongly implicated (i.e., can be considered as one the main factors implicated in injury occurrence) in injury occurrence. Accordingly, TL monitoring, focusing on relevant variables such as sprinting thought a data-informed approach, represent a necessary and relevant practice to optimize training prescription (aiming to adapt players to withstand match demand) and indirectly reduce injury risk. In shaping our framework's rationale, we adhered to the multifactorial and complex nature of injuries proposed by Bittencourt et al., according to which the interaction between specific risk factors is linked to injury occurrence. Additionally, we referenced the holistic perspective outlined by Windt and Gabbett (227), which posits that load contributes to injury risk by exposing players to injury situations while providing positive and negative adaptations, ultimately making athletes either stronger (capable of coping with high loads) or weaker (not adapted to cope with high loads).

Through our conceptual perspective, which considers the player's profile, overall fitness status, and tissue load response based on intrinsic tissue characteristics and strength derived from tissue adaptation, we aim to provide a comprehensive understanding of acute injury events to facilitate the implementation of appropriate prevention strategies. This is achievable through a data-informed approach supported by knowledge of applied physiology and training methodology. Worth noting, data-informed approach is in contrast to data-driven approaches, which are not supported by any appropriately validated prognostic models for athletic injury risk assessment.

- Training practices primarily aim to adapt players to withstand match demands while reducing injury occurrence. To achieve optimal physiological and match-related adaptations, we conceptualized that players need to adapt to two main factors related to intensity and volume, as depicted in Figure 3.30. Worth noting, two relevant training variables such as frequency and density should be considered during the training prescription process. However, we highlighted that our framework has not included frequency and density as both can be considered two complementary variables of volume and intensity. Our framework illustrates that to mitigate injury risk, practitioners must mainly consider both acute mechanical load tissue exposure (AMLTE) and muscle tolerance to load (MTTL). AMLTE represents the

highest acute mechanical stress that muscle tissue is exposed to within a specific short period, such as the maximal effort exerted during a sprint, which could lead to a non-contact injury if the tissue has not adapted to such demands. Meanwhile, MTTL indicates the muscle tissue's ability to tolerate a given load accumulated over time considering both short and long periods. The negative effects of fatigue on injury risk are well-documented, and a muscle that is not metabolically adapted is vulnerable to injury.

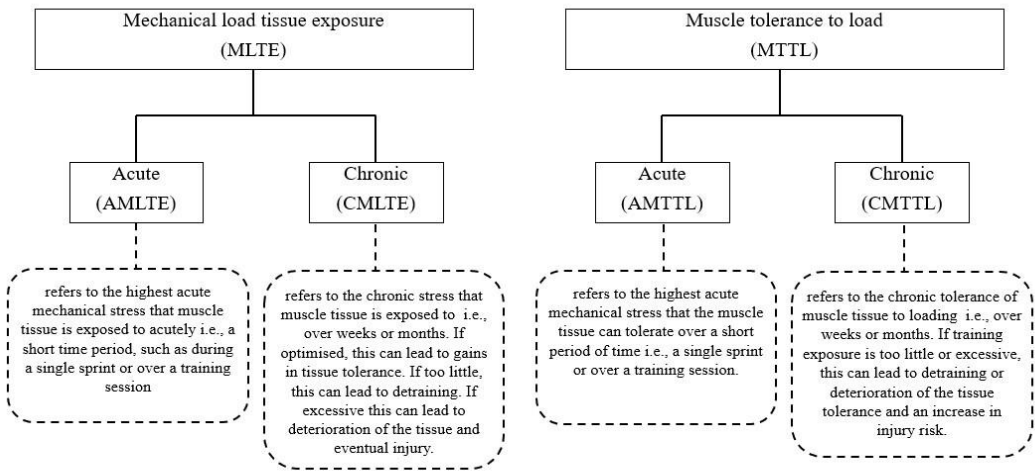


Figure 3.30 Non-contact injury risk prevention strategies: a conceptual framework
 Figure shows our framework illustrates that to mitigate injury risk, practitioners must mainly consider both *acute mechanical load tissue exposure (AMLTE)* and *muscle tolerance to load (MTTL)*. AMLTE represents the highest acute mechanical stress that muscle tissue is exposed to within a specific short period, such as the maximal effort exerted during a sprint, which could lead to a non-contact injury if the tissue has not adapted to such demands. Meanwhile, MTTL indicates the muscle tissue's ability to tolerate a given load accumulated over time considering both short and long periods. The negative effects of fatigue on injury risk are well-documented, and a muscle that is not metabolically adapted is vulnerable to injury.

As illustrated in Figure 3.31, when a player is poorly adapted (e.g. if they have a low fitness level or weakness), their muscle load tolerance is low, increasing the risk of injury. Conversely, a strong player (e.g. a player with a high fitness level and good adaptation) has a low risk of injury due to their high load tolerance. Figure 3 depicts the conceptual relationship between load, player fitness status, and injury risk. Table 1 and Figure 2 illustrate the implications of external load on injury risk for both weak and strong players.

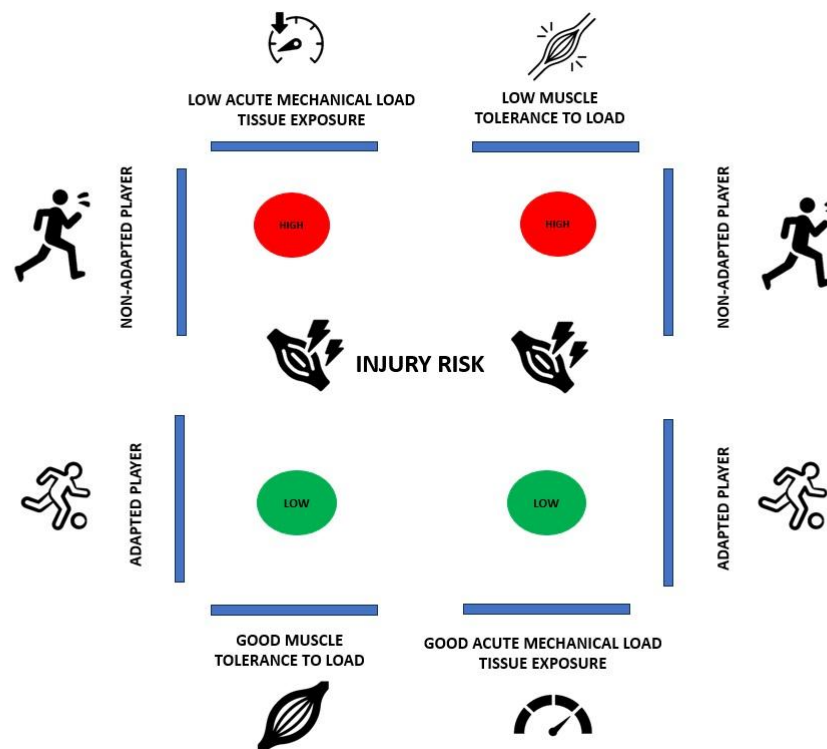


Figure 3.31 Strong vs weak athlete and non-contact injury risk: a conceptual framework

Figure 3 depicts the conceptual relationship between load, player fitness status, and injury risk. When a player is poorly adapted (e.g. if they have a low fitness level or weakness), their muscle load tolerance is low, increasing the risk of injury. Conversely, a strong player (e.g. a player with a high fitness level and good adaptation) has a low risk of injury due to their high load tolerance.

To achieve optimal player adaptation (i.e. the highest fitness level), practitioners must administer appropriate TL while considering both AMLTE and MTTL to protect players from match stimuli and reduce injury and reinjury risk. The conceptual framework outlined above can be better understood by envisioning a real-world scenario that a professional, such as a rehabilitation coach, might encounter. The rehabilitation process aims to adapt players to withstand match demands, such as reaching peak speed and covering HSR distances. By gradually progressing through physiological demands and training methodologies, players reach a level of adaptation that enables them to cope with intense training stimuli. Upon returning to official matches, players' muscular tissues must be sufficiently adapted to withstand their peak speed and sustain HSR distances based on previous match data. Therefore, before declaring a player fit for an official match, the rehabilitation coach and medical staff must ensure that the player's tissues can withstand maximum effort even if only for a short duration.

6. HOW CAN DATA MITIGATE INJURY OCCURRENCE IN SOCCER? A NEW FRAMEWORK OF A DATA-INFORMED APPROACH AND DECISION-MAKING TO REDUCE INJURY RISK

Load management is widely recognized as one of the primary non-contact injury prevention strategies in soccer (132, 216, 227, 235). Key factors for effective load management include training methodology, coach experience, and evidence-based knowledge, such as knowledge of sports demands and physiology, which collectively inform appropriate training prescriptions (2, 216, 218, 503). External and internal load monitoring practices are commonplace in elite soccer and offer invaluable feedback for modifying training regimens and managing external load effectively by employing a data-informed approach. To delve into the relationship between training monitoring and training prescription we refer readers to the review by Pillitteri et al., (6)

Figures 3.32–3.34 illustrate a data-informed framework depicting the relationship between training prescription and training monitoring prescription in soccer. Specifically, monitoring metabolic, HSR, and neuromuscular external load indicators (comprising both volume and intensity) provides practitioners with essential information on soccer physical performance, representing key factors that should be considered in training prescriptions. This allows the management of training prescriptions to be altered or adjusted based on collected data. For example, integrative work may be implemented after training sessions to achieve training goals, and subsequent training days' prescriptions can be adjusted as necessary.

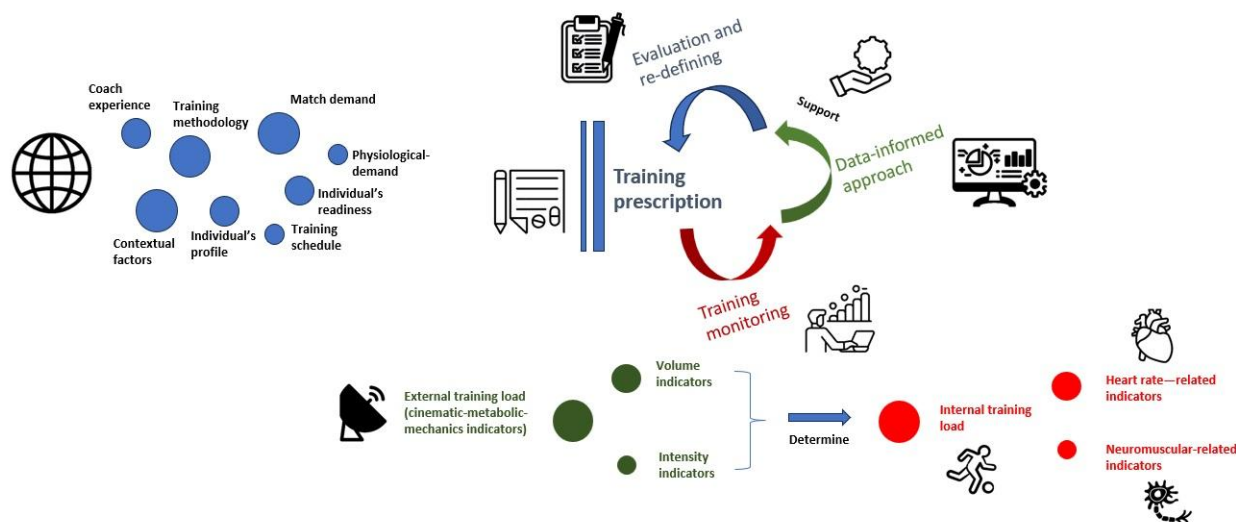


Figure 3.32 Evidence-based training prescription: a conceptual framework

Figures 4 illustrate a data-informed framework depicting the relationship between training prescription and training monitoring prescription in soccer. Specifically, monitoring metabolic, HSR, and neuromuscular external load indicators (comprising both volume and intensity) provides practitioners with essential information on soccer physical performance, representing key factors that should be considered in training prescriptions. This allows the management of training prescriptions to be altered or adjusted based on collected data

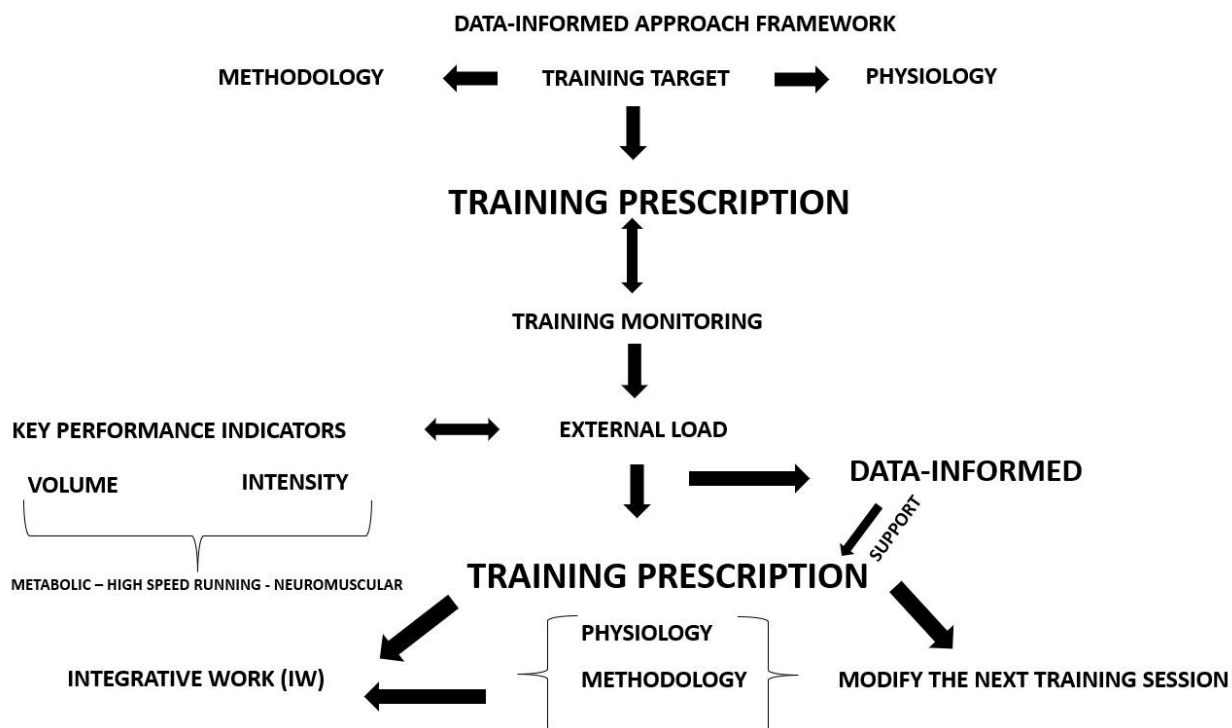


Figure 3.33 Decision-making based on a data-informed approach: a conceptual framework

The training prescription is supported by Data-informed. In fact, both external and internal load data provide information to make an appropriate decision on the training prescription. In particular, it may be possible to increase the load through an Integrative Work (IW) at the end of the section, as well as modify the next training section by increasing or decreasing the load (considering the individualization process in which the load is managed for each player).

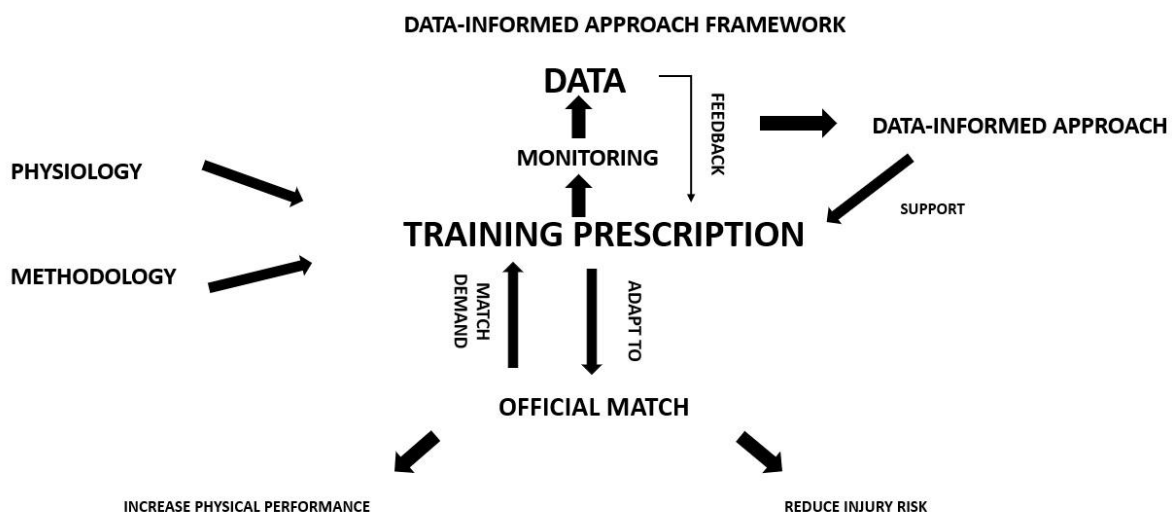


Figure 3.34 Data-informed approach to training prescription: a conceptual framework

Figure 6 shows the implication of data-informed approach on training prescription. Training prescription should be mainly based on training methodology (including training principles), physiology knowledge and the information derived from match-demand (e.g., GPS data). Data support training prescription providing useful feedback to make a decision on training load management.

Table 3.13-3.14 provides an example of how a data-informed approach can be applied in a real-world soccer scenario. The data-informed approach promotes optimal load management, as it enables modifications to training prescriptions based on feedback derived from monitoring data. Our framework emphasizes the supportive role of data-informed approaches in training prescription. However, relying exclusively on a data-informed approach for training prescription may introduce errors or cognitive biases, such as focalism, as discussed in previous sections (502, 544, 550).

A sound training practice should begin with an understanding of applied physiology and training methodologies, and data should be collected during monitoring to provide feedback for effective training management. Through the feedback provided by data, it is possible to profile drills, players, and match days (within the microcycle) and to understand the physical demands of soccer (including monitoring official matches). However, data-informed programming can be susceptible to

conceptual errors if the process is driven solely by numbers, which should be viewed as supportive rather than prescriptive.

	Table 3.13, Relationship between High-Speed running/Peak Speed, and Injury Risk considering the differences between strong and weak players: an example from the microcycle										
	PLAYER A STRONG PLAYER										
	1° MICROCYCLE					2° MICROCYCLE					
	MD-4	MD-3	MD-2	MD-1	MD	MD+2/-5	MD+3/-4	MD+4/-3	MD+5/-2	MD+6/-1	MD
DISTANCE >25.2 Km/h (m)	40	190	120	30	210	40	90	200	100	20	250
PEAK SPEED (Km/h)	26	33	26	29	33	26	28	35	30	29	34
	PLAYER B WEAK PLAYER										
	1° MICROCYCLE					2° MICROCYCLE					
	MD-4	MD-3	MD-2	MD-1	MD	MD+2/-5	MD+3/-4	MD+4/-3	MD+5/-2	MD+6/-1	MD
DISTANCE >25.2 Km/h (m)	0	30	0	0	70	0	20	40	10	0	200
PEAK SPEED (Km/h)	23	27	26	27	29.5	26	25	28	27	28	31

Table 3.14, A data-informed approach based on the external load data (sprinting) collected in the microcycle considering playing position	
MD+3/-3 Aim: development of Sprinting ability Target fullback: 180m (distance >25.2 Km/h)	
PLAYER A	PLAYER B
Playing position: fullback Reference value (official match): Distance covered in Sprinting (>25.2 Km/h): 200m Peak speed reached: 34 Km/h EXTERNAL TRAINING LOAD VOLUME Distance covered in Sprinting (>25.2 Km/h): 90m Peak speed reached: 27.2 Km/h (80% peak speed) DECISION MAKING BASED ON DATA INFORMED: - INTEGRATIVE WORK AT THE END OF THE TRAINING 3X30m SPRINT 3X40m SPRINT	Playing position: fullback Reference value (official match): Distance covered in Sprinting (>25.2 Km/h): 200m Peak speed reached: 34 Km/h EXTERNAL TRAINING LOAD VOLUME Distance covered in Sprinting (>25.2 Km/h): 250m Peak speed reached: 32.3 Km/h (80% peak speed) DECISION MAKING BASED ON DATA INFORMED: - NO INTEGRATIVE WORK - MANAGE LOAD (VOLUME) IN THE NEXT TRAINING SESSION
OUTCOME: Based on the reference value (physical demand derived from official match), player A shows low distance covered in Sprinting (>25.2 Km/h). Accordingly, additional integrative work (sprint) will be administered at the end of the training session.	OUTCOME: Based on the reference value (physical demand derived from official match), player A shows excessive distance covered in Sprinting (>25.2 Km/h). Accordingly, the load will be managed in the next training session.

CONCLUSION

Injuries, particularly hamstring injuries, represent a high-cost burden for elite soccer clubs.

With the aim of translating research into practical insights for practitioners, we have summarized the main findings on non-contact injury in soccer, and described the different conceptual frameworks of soccer injuries. Finally, we present a new conceptual framework on non-contact soccer injuries focusing on the contribution offered by data-informed approaches to implement non-contact injury prevention strategies.

Hamstring injuries have been linked to HSR and sprinting activities, primarily due to the high eccentric loading experienced during the late swing phase and early stance phase. However, the relationship between TL and injury occurrence is complex, and attributing a cause-effect relationship between a single factor and injury may be prone to cognitive biases.

Predicting, associating, or establishing a statistical relationship between a risk factor and injury occurrence lacks the explanatory power necessary for causal inferences, and therefore fails to explain why an athlete was injured at a particular time and under specific circumstances. Nonetheless, recognizing potential injury risk factors such as HSR can help practitioners exercise caution in real-world scenarios, such as HSR-related training sessions.

We have developed a conceptual framework that highlights two main factors related to intensity and volume: acute mechanical load tissue exposure (AMLTE) and muscle tolerance to load (MTTL). We have done this to mitigate the risk of injury and reinjury, drawing from previous contributions of conceptual frameworks, qualitative research, and field experience. By focusing on both AMLTE and MTTL, practitioners can move towards optimal "protective" player adaptation (i.e. improving the athlete's fitness level to withstand match demands) and reduce injury risk.

In a real-world context, coupling optimal training practices with appropriate TL management should be regarded as the best prevention strategy to mitigate injury risk. Assessing an athlete's fitness status (i.e. whether their tissues are adapted to withstand external stimuli) to administer a significant load, such as HSR, may facilitate effective injury prevention strategies, considering that daily invasive assessments of physiological properties are not feasible. Consequently, employing an indirect method, such as a data-informed approach alongside sound training methodology (while also considering applied physiology), promotes the understanding of whether an athlete can tolerate the EL that induces an appropriate internal response (i.e. load tolerance).

Data-informed approaches should be viewed as supportive tools for training prescription, as they help achieve optimal adaptation and increase a player's physical status, thereby potentially reducing injury risk. By exclusively focusing on data while neglecting both applied physiology in sports and training methodology, practitioners may commit reasoning errors (cognitive biases), which may not foster injury prevention. Indeed, due to the complex nature of non-contact hamstring injuries, along with the absence of an appropriately validated prognostic model for predicting injury risk, practitioners should be aware of their underlying biases. This is particularly important to consider in cases where selected interventions restrict athletes (e.g., training, or competitive exposure), especially when such interventions are imposed on athletes against their will, and without robust athletic injury predictions as a justification.

The cause-effect relationship regarding injury needs to be implemented through accurate scientific methods such as RCTs or causative inference tools such as frameworks, models, or DAGs. In the future, it may be useful to optimize machine learning approaches methodology to explore the

interactions between various risk factors and intrinsic athlete-related aspects that may concurrently contribute to acute injury events.

3.8 Discussion

Over the past decade, the scientific community has devoted considerable attention to unravelling the intricate relationship between training load and performance outcomes in sports. This relationship is not only dynamic but also multifactorial, involving numerous variables that interact in complex ways. Traditional statistical methods, while foundational, have shown limitations in fully capturing these complexities, particularly given the vast amounts of data generated by modern performance monitoring technologies. This necessitates the use of advanced analytical tools like artificial intelligence (AI) and machine learning (ML), which offer the potential to uncover deeper, more nuanced insights.

The application of machine learning in sports science has opened new avenues for understanding the interplay between external and internal load, performance outcomes, and injury risk. By leveraging ML's capacity to handle multidimensional datasets, researchers can explore non-linear relationships and predictive patterns that were previously inaccessible through conventional methods. This shift in analytical paradigms has led to significant strides in the field, yet gaps remain that need addressing to fully integrate these insights into practical training and injury prevention strategies.

This chapter synthesizes findings from multiple studies that collectively advance our understanding of training load management in soccer. Each study contributes unique perspectives, yet together they offer a holistic view of how training load, recovery, performance, and injury risk are interconnected.

Study Integration and Holistic Insights

The first study highlighted the role of ML in profiling player positions based on external load data from various drills and match scenarios. This approach enables a granular analysis of the physical demands placed on players in different positions, providing critical insights for designing position-specific training programs. These findings underscore the importance of tailoring training

interventions to the unique physiological demands of each role, optimizing performance while minimizing injury risk.

The introduction of a novel load and performance score system in the second study simplifies the complex task of monitoring and interpreting microcycle training loads. By aggregating various external load indicators into a cohesive summary measure, this system allows for more straightforward comparisons between players and sessions. This innovation facilitates data-driven decision-making, enabling coaches to balance training intensity and volume effectively, thus optimizing performance and recovery.

The third study's focus on intensity within a standard microcycle offers valuable insights into the physiological and metabolic demands of different training sessions and match days. By identifying key intensity indicators that distinguish match-day types, this study provides a framework for periodizing training loads, ensuring that players are adequately prepared for the varying demands of competition. Moreover, the consideration of positional variations highlights the necessity of a personalized approach to training, which is essential for both performance enhancement and injury prevention.

Finally, the investigation into the relationship between training load, recovery, and availability adds a critical dimension to the discussion. This study reveals the intricate feedback loop between training load and recovery, emphasizing how these elements influence each other both within the same day and across consecutive days. The identification of availability as a mediating factor in this relationship offers new perspectives on how to optimize training schedules to enhance recovery and sustain high levels of performance throughout a season.

A Holistic Framework for Training Load Management

Collectively, these studies contribute to a more comprehensive understanding of how various components of training load interact to influence performance and injury outcomes. A holistic framework emerges, one that integrates multiple dimensions of athlete monitoring:

Individualized Training Programs: By considering the unique demands of different playing positions and drills, practitioners can design training programs that address specific physical and metabolic requirements, thereby enhancing performance and reducing the risk of injury.

Simplified Load Monitoring: The use of summary indicators for training load facilitates clearer communication and decision-making, allowing coaches to manage training intensity and volume more effectively.

Dynamic Intensity Management: Understanding the intensity demands of different training sessions and matches enables more precise periodization, ensuring players are optimally prepared for competition while minimizing overtraining risks.

Recovery Optimization: Recognizing the interplay between training load and recovery, and the role of availability as a mediating factor, supports the development of training schedules that enhance recovery and sustain performance across a season.

The integration of these studies highlights the transformative potential of machine learning in sports science. By providing a more holistic and nuanced understanding of training load dynamics, ML enables practitioners to adopt a data-informed approach to training management. This approach not only enhances performance outcomes but also contributes to more effective injury prevention strategies.

Future research should continue to explore the multifactorial nature of training load and its implications for performance and injury. Longitudinal studies that incorporate real-time data analysis and predictive modelling could further refine our understanding of these relationships. Additionally, expanding the scope to include psychological and environmental factors would offer a more comprehensive view of athlete health and performance.

In conclusion, the integration of findings from multiple studies into a cohesive framework demonstrates the value of a holistic approach to training load management. By leveraging advanced analytical techniques, sports science can move towards more personalized, data-driven practices that optimize athlete performance and well-being, ultimately bridging the gap between research and practical application.

Chapter IV - Personal skills and achievements

4.0 Learning experiences and skills at the Sport and Exercise Sciences Research Unit

In the local unit where the PhD course was mainly followed research projects were used as a training experience and a range variety of activities were performed. Different performance tests were applied to measure strength (Handgrip and T-force), muscular endurance (Push and pull-up test to exhaustion), balance (Y-balance test), jump performance (standing broad jump and Optojump measurements), anaerobic capacity (Wingate test), ROM (Gyko inertial sensor). Also, body composition analysis was carried out using body impedance analysis (BIA - AKERN 101 - AKERN SRL, RJL Systems, Detroit, USA) was used. HRV variables were also assessed and needed HR data to be collected first with a Polar H10 sensor and then calculated with Kubios software. Some questionnaires were also implemented such as the SF-36 for HRQoL measurements and IPAQ for PA levels. All the abovementioned tests were first learnt and then practised and only after a satisfactory amount of practice, which could have ensured the reliability of the measures, have been applied in the research projects.

During the 3 years, I was also involved in the development of systematic reviews and meta-analyses which require a conspicuous amount of knowledge on research methodologies as well as specific review methodology and risk of bias assessment. This expertise was learned to complete the study and offer specific insights into general research methodology. It should be also considered that statistical analysis must be performed, as well as, the creation of graphs. A variety of software was explored to implement statistical analysis (SPSS, Jamovi, GraphPad PRISM, STATISTICA and R). However, Jamovi and GraphPad were mainly implemented in the presented research projects. Different software may have different statical capabilities and have been properly explored to ensure correct calculations.

Worth noting, I Started a fundamental collaboration with Professor Alessio Rossi, head of data science at Olympique de Marseille and expert in Machine Learning. Alessio provides me a great support to employ sophisticated analysis such as time series and machine learning thought Python software. His paramount contribution allowed me to carrying on machine learning studies and learn about theories on this complex and fascinating topic.

4.2 Learning experiences and skills at the Palermo FC

During the three-year-long PhD course in Health Promotion and Cognitive Sciences, I was able to work as sports scientist and fitness coach at Palermo FC, Italian professional first team, participating in Serie B championship (second division). Within this high-level context, I was able to participate in ongoing activities of exercise interventions related to training in soccer. In detail, as a sports sciences and physical trainer/fitness coach, it was essential to learn how to train soccer players focusing on training load monitoring who require the ability to implement specific devices such as Global Positioning System (GPS) and dedicated software. In Particular, to monitoring the external load I dealt with a wearable tracking device with kinematics, physiological and environmental sensors, the GPS (StatSport – Apex v3.2 Pro Series - 10 Hz multi-GNSS augmented unit incorporating a 3d gyroscope and 3d accelerometer and HR sensor). The software dedicated is Sonra v5.

Moreover, external load data were also collected through a wearable inertial sensor (TalentPlayers TPDev, firmware version 1.3). This ISD is a small wearable device integrating a six degrees of freedom (Micro Electro Mechanical Systems, MEMS) inertial sensor, capable of providing real-time acceleration and rotation data along three orthogonal axes at a frequency of 100 Hz per channel. It is designed to be worn on the lower leg using an elastic band. All data were acquired by the TalentPlayer mobile app (software version 1.0.7) and uploaded to the TalentPlayers cloud.

Internal load has been assessed through HR measurement and the implementation of Rating of Perceived Effort, RPE scale. Training Load (TL) was calculated according to the session-RPE method of Foster et al. (2001). Specifically, TL is given by multiply the duration (minutes) and each RPE training.

To estimate the players' state of recovery the TQR scale was used, while wellbeing has been assessed through the McLean (2010) scale that includes Fatigue, Muscle Soreness, Mood, Stress, Sleep.

Strength training: yoyo-isoinertial devices – Desmotec; Bio strength Leg Press – Technogym; – Keiser machine; VALD system (ForceDecks, Nordboard, ForceFrame, SmartSpeed – software Vald Hub); blood flow restriction device.

Moreover, I have used Power BI that represent a collection of software services, apps, and connectors that work together to turn unrelated sources of data into coherent, visually immersive, and interactive

insights. Data might be an Excel spreadsheet, or a collection of cloud-based and on-premises hybrid data warehouses. Power BI lets easily connect to data sources, visualize and discover what's important, making valuable report useful to informed-making process. The fundamental collaboration with the engineer (and my friend) Francesco Lunetta (Software Engineering Manager-Microsoft) who provided the support to create the structure and architecture of the data, has allowed the creation of a real data management software relating to training load in soccer. This allowed me to create a daily report as well as different kind of requested report to support training prescription and player's management through the informed-making approach. This practice, commonly known as data-informed approach, represent a challenge to improve the players physical performance while reducing injury risk.

This daily activity has been carried out under the supervision of Tindaro Bongiovanni (Head of Performance), head of fitness coaches (Professor Marco Petrucci/season 2023-2024 and Professor Fabio Spighi/season 2024-2025). The ongoing and daily work within a Multidisciplinary team (MDT) improved me skills on team working, management and communication, collaboration, and coordinated planning. Indeed, MDT in healthcare is a group of professionals from various disciplines who collaborate to provide comprehensive care for players. These teams are designed to bring together the unique skills and expertise of each member such as doctors, physiotherapists, nutritionist, physical coach, rehab coach, head of performance, sports scientist, strength and conditioning coach, ultimately resulting in improved patient outcomes. Each member of the team contributes their specific knowledge and skills to develop a cohesive care plan tailored to the needs of the individual players.

4.3 International period and international collaborations

During the three-year-long PhD course in Health Promotion and Cognitive Sciences, I was able to spend six months (between June 2023 and December 2023) abroad at the University of Coimbra – Faculty Of Sport Sciences And Physical Education. Within this laboratory, I was able to participate in ongoing activities of exercise interventions related to training in soccer. In detail, as a sports sciences and physical trainer/fitness coach, it was essential to learn how to train soccer players focusing on training load monitoring who require the ability to implement specific devices such as Global Positioning System (GPS) and dedicated software. These elements are essential when the aim is to obtain improved physical performance while reducing injury risk. Once the ability to train

professional soccer players, a range variety of testing skills were learned/improved. A short list of the tests and instruments used are listed below:

- VO2 max testing on treadmill or bike: ParvoMedics metabolic gas exchange analyser
- 1/10 RM strength testing on machines or free weights
- Yo-Yo Desmotec – isoinertial devices
- Strength Functional devices: Keiser Machines
- GPS devices: external training load
- RPE Scale and HR: internal training load
- Wellness and Recovery scale
- On-Field aerobic test: Mognoni, Gacon, HIT, Yo-Yo Intermittent Recovery test

All the abovementioned tests/devices represent an inestimable knowledge of testing procedures among professional soccer players populations.

The research under the supervision of Professor Hugo Sarmiento and Filipe Manuel Clemente brought to the finalization of 2 manuscripts. In particular, the continuous comparison and sharing of ideas, projects, as well as the continuous support provided supervisors has allowed my human and professional growth. Finding great competence, availability, humility, improving my personal skills has been stimulating has allowed me to carry forward a complex project.

4.4 Other published papers

Some published papers were not reported in previous chapters are shown below:

1. Ficarra, S., Thomas, E., Pillitteri, G., Migliore, D., Gómez-López, M., Palma, A., & Bianco, A. (2022). CHANGES IN QUALITY OF LIFE, STRENGTH AND HEART RATE VARIABILITY AFTER 4-WEEKS OF SUPERVISED ONLINE BURPEES TRAINING DURING THE COVID-19 QUARANTINE IN HEALTHY YOUNG ADULTS: A PILOT STUDY. *Kinesiology*, 54(1), 116-125.
2. Di Stefano V, Thomas E, Giustino V, Iacono S, Torrente A, Pillitteri G, Gagliardo A, Lupica A, Palma A, Battaglia G, Brighina F. (2022). Motor Conduction Studies and Handgrip in Hereditary TTR Amyloidosis: Simple Tools to Evaluate the Upper Limbs. *Front Neurol*. 2022 Feb 28;13:835812.
3. Di Stefano V, Thomas E, Alonge P, Giustino V, Pillitteri G, Leale I, Torrente A, Pignolo A, Norata D, Iacono S, Lupica A, Palma A, Battaglia G, Brighina F. (2022). Patisiran Enhances Muscle Mass after Nine Months of Treatment in ATTRv Amyloidosis: A Study with Bioelectrical Impedance Analysis and Handgrip Strength. *Biomedicines*. 2022 Dec 27;11(1):62.
4. Petrigna L, Petta A, Giustino V, Leale I, Pillitteri G, Palma A, Zangla D, Battaglia G. (2023). A scoping review on how physical fitness is evaluated in sitting volleyball players. *J Sports Med Phys Fitness*. 2023 Mar;63(3):430-435.
5. Leale I, Petrigna L, Giustino V, Pillitteri G, Barbieri RA, Palma A, Musumeci G, Battaglia G. (2023). A standard operating procedure for the physical performance analysis of wheelchair fencer: a scoping review. *J Sports Med Phys Fitness*. 2023 Nov;63(11):1175-1181.

6. Izadi M, Pillitteri G, Thomas E, Battaglia G, Bianco A, Bellafigliore M. Sex differences in the determination of prescribed load in ballistic bench press. *Front Physiol.* 2024 Jan 12;15:1293044.
7. Pillitteri G, Thomas E, Battaglia G, Navarra GA, Scardina A, Gammino V, Ricchiari D, Bellafigliore M. (2021). Validity and Reliability of an Inertial Sensor Device for Specific Running Patterns in Soccer. *Sensors (Basel).* 2021 Oct 31;21(21):7255.
8. Clemente, F., Pillitteri, G., Vieira, L. H. P., Rabbani, A., Zmijewski, P., & Beato, M. (2024). Balancing the load: A narrative review with methodological implications of compensatory training strategies for non-starting soccer players. *Biology of Sport*, 41(4), 173-185.
9. Giustino V, Bonaventura RE, Messina G, Patti A, Pillitteri G, Pajaujiene S, Paoli A, Palma A, Bianco A, Oliveri M, Battaglia G. (2024). Acute effects of prismatic adaptation on penalty kick accuracy and postural control in young soccer players: A pilot study. *Heliyon.* 2024 Apr 30;10(9):e30515.
10. Pillitteri G, Giustino V, Petrucci M, Rossi A, Leale I, Bellafigliore M, Thomas E, Iovane A, Palma A, Battaglia G. (2023). Match Load Physical Demands in U-19 Professional Soccer Players Assessed by a Wearable Inertial Sensor. *J Funct Morphol Kinesiol.* 2023 Feb 7;8(1):22.
11. Pillitteri G, Giustino V, Messina G, Petrucci M, Rossi A, Bellafigliore M, Iovane A, Thomas E, Bianco A, Palma A, Battaglia G. (2023). Comparison of external load indicators between official matches and sport-specific training in semi-professional soccer players: focus on intensity and strength. *J Sports Med Phys Fitness.* 2023 Mar;63(3):385-393.
12. Pillitteri G, Giustino V, Petrucci M, Rossi A, Bellafigliore M, Thomas E, Iovane A, Bianco A, Palma A, Battaglia G. (2023). External load profile during different sport-specific activities in semi-professional soccer players. *BMC Sports Sci Med Rehabil.* 2023 Feb 22;15(1):22

Chapter V – Conclusion

5.1 Conclusion

This thesis aimed to provide a theoretical and practical contribution on the complex relationship between training load and training outcomes based on the gaps identified in the literature.

In the first section, we dealt with training load monitoring (including both intensity and volume) deepening the conceptual knowledge about intensity while focusing on the main practice performed by practitioners concerning the information derived from training load monitoring to training prescription. In detail, we have conceptualized and defined the intensity in soccer providing evidence-based information. In the same way, we have reported insight on training prescription starting from the support of training monitoring providing theoretical information and practical examples. In this way, we have clarified paramount concept in training prescription in soccer.

In the second section of this thesis, we delve into the implication of machine learning to understand the relationship between training and competition considering playing position to enhance physical performance and reduce injury risk. In detail, ML provided valuable insight on profiling playing position considering different drills typologies and official match. We have also focused on microcycle assessment starting from a new score computed through ML approach as well as considering the intensity indicators. In the same way, we have investigated the association between training load and recovery implementing ML approach, founding promising results.

To offer a theoretical overview on hamstring injuries we offered a narrative review with conceptual framework. We reported practical insight on data-informed process to mitigate the risk of injury by managing the training load (sprinting distance).

In conclusion, this thesis offered promising results concerning the current understanding around the training load monitoring, physical performance and training prescription, focusing on the implication of machine learning on training load, physical performance analysis, and injury risk in soccer players. Based on our results, we affirm that Machine learning has become an essential tool for analyzing and managing the vast amounts of data generated through the daily monitoring of players. Unlike traditional analytical methods, ML enables the identification of nuanced and complex relationships between variables. It can provide valuable predictions and insights, helping to define player roles, determine intensity levels, and classify the types of physical stimuli, thereby offering a more comprehensive understanding of physical performance and training target. In the future, this approach is expected to become more robust and refined, delivering even more precise and reliable

results. While the direction of research is increasingly leaning toward artificial intelligence and machine learning, several limitations remain, particularly in their application to soccer, where a variety of methodological approaches have been utilized. Moreover, many studies fail to provide detailed information about the methodologies employed, which stands as a significant limitation in advancing the field.

This thesis aimed to provide a multifaceted exploration of the complex relationship between training load and training outcomes, offering both theoretical insights and practical applications. By addressing the identified gaps in the literature, this research contributes significantly to the fields of sports science, athletic performance management, and injury prevention, particularly in the context of soccer. The study is structured around several key themes: training load monitoring, the practical application of data in training prescription, the use of machine learning (ML) in sports performance analysis, and injury risk mitigation strategies.

Training Load Monitoring: Conceptual and Practical Insights

The first major contribution of this thesis lies in the detailed examination of training load monitoring, particularly focusing on the dual aspects of intensity and volume. The research offers a refined conceptualization of intensity, which is a critical yet often ambiguously defined component of training. By systematically defining intensity in the context of soccer, the thesis provides a solid foundation for practitioners to better understand and measure this parameter.

This section further investigates how the data derived from monitoring tools can be translated into actionable training prescriptions. By elucidating the relationships between monitored training load variables and their practical applications, the research bridges the gap between data collection and on-field training strategies. This clarity is essential for practitioners aiming to optimize player performance and manage training stress effectively. The insights offered in this section not only refine the theoretical understanding of training load but also present a framework for its practical application, making it a valuable resource for coaches and sports scientists alike.

Machine Learning in Soccer: Enhancing Performance and Reducing Risk

A significant portion of the thesis is dedicated to exploring the application of machine learning (ML) in understanding the complex interactions between training variables and competitive

performance. This represents a cutting-edge contribution to sports science, where ML's potential to process and analyse vast datasets can uncover patterns and relationships that traditional methods may overlook.

The thesis delves into the role of ML in profiling players based on their positions and the types of drills they engage in, alongside official match data. This approach provides a nuanced understanding of how different training stimuli affect players in various roles, allowing for more tailored and effective training programs. The use of ML also extends to the assessment of the microcycle, where a novel score derived through ML algorithms integrates multiple intensity indicators. This innovative approach offers a more comprehensive and dynamic assessment of player readiness and fatigue, which is critical for optimizing performance and minimizing the risk of overtraining.

Furthermore, the research investigates the association between training load and recovery using ML models. By analysing how different training loads impact recovery times and subsequent performance, the thesis contributes valuable knowledge to the development of more personalized and effective recovery protocols. The findings suggest that ML can play a pivotal role in enhancing player welfare by informing data-driven decisions that balance performance with injury prevention.

Injury Prevention: A Data-Informed Approach to Managing Hamstring Injuries

In addition to performance optimization, this thesis addresses the critical issue of injury prevention, focusing on hamstring injuries, which are prevalent in soccer. Through a comprehensive narrative review, the research constructs a conceptual framework for understanding the factors contributing to hamstring injuries. It emphasizes the importance of managing sprinting distances—a key component of training load—as a preventive strategy.

The practical insights offered in this section highlight the potential of data-informed approaches to mitigate injury risks. By leveraging training load data, practitioners can identify players at heightened risk and adjust training regimens accordingly. This proactive approach is instrumental in reducing the incidence of injuries, thereby preserving player health and availability for competition.

Integrative Contributions and Future Implications

In synthesizing these various strands of research, this thesis offers a holistic view of training load management, performance optimization, and injury prevention. It demonstrates how theoretical

concepts can be operationalized through advanced analytical techniques, providing a robust framework for future research and practical application.

One of the key contributions of this thesis is the demonstration of ML's utility in sports science. By applying ML to real-world data, the research showcases how these techniques can enhance our understanding of complex training dynamics. The ability of ML to process and interpret large datasets enables a more precise and individualized approach to training and recovery, setting a new standard for data-driven decision-making in sports.

The thesis also identifies several areas for future research, particularly in refining ML models and improving their generalizability across different sports contexts. While the results are promising, the study acknowledges the need for further exploration of methodological consistency and transparency in ML applications. Addressing these challenges will be critical for advancing the field and ensuring that the benefits of ML are fully realized in practical settings.

Conclusion

In conclusion, this thesis makes substantial contributions to the field of sports science by deepening the understanding of training load and its implications for performance and injury prevention. It highlights the transformative potential of machine learning in managing and interpreting complex data, paving the way for more personalized and effective training strategies. As the field continues to evolve, the insights provided in this research will serve as a foundation for future advancements, offering a comprehensive guide for practitioners and researchers alike.

5.2 Limitation

While machine learning (ML) offers a powerful approach to analysing complex and multidimensional datasets in sports science, its application is not without significant limitations. One of the primary challenges is the lack of external validation in most studies, which undermines the generalizability of ML models across different populations, sports, and competition levels. This limits the practical utility of these models for real-world applications.

Another critical issue is sample size inadequacy. ML algorithms are often "data-hungry," requiring large datasets to function effectively and avoid overfitting. Overfitting occurs when a model becomes too tailored to the specifics of the training data, reducing its ability to generalize to new data.

In sports science, the small sample sizes commonly available exacerbate this problem, leading to unreliable predictions and reduced model robustness.

Additionally, methodological transparency remains a significant concern. Many studies fail to report crucial details, such as hyperparameter tuning, algorithms used, or the rationale behind model selection. Without this information, it becomes challenging to reproduce studies, validate results, or critically assess the reliability of the models. This lack of transparency is further compounded by the limited use of standardized reporting guidelines, such as TRIPOD for machine learning (TRIPOD-AI), which is still in development.

Another limitation is the tendency to dichotomize continuous variables or handle nonlinear relationships inadequately. Such practices can lead to the loss of valuable information and reduce the predictive accuracy of models. ML methods are well-suited to address nonlinear relationships, but improper preprocessing of data or arbitrary categorizations can diminish their effectiveness.

Finally, the complexity of ML models often results in a lack of interpretability, making it difficult for practitioners to understand the reasoning behind predictions. This "black-box" nature can reduce trust in the models and hinder their adoption in practical settings. Moreover, the computational demands of ML approaches and the expertise required to implement them effectively can act as barriers to their widespread use in sports science.

Addressing these limitations will require a concerted effort to improve data quality, increase methodological rigor, and establish standardized practices for reporting and validating ML models. Collaborative efforts across institutions and disciplines could also help overcome sample size limitations and foster the development of robust, clinically useful models for injury prevention and performance optimization.

Given the above-mentioned causes, this thesis presents intrinsic limitations due to the machine learning methods used while narrative reviews with conceptual frameworks reported equally present some limitations.

Narrative reviews in sports science face several challenges that can limit their reliability and utility. A primary concern is their inherent subjectivity and susceptibility to bias. Since narrative reviews heavily rely on the expertise and judgment of the authors, there is a risk that the selection and interpretation of studies may be partial or incomplete. Unlike systematic reviews, narrative reviews do not follow strict methodological protocols, making them difficult to replicate. This lack of reproducibility undermines the verification of their findings and reduces their reliability.

Similarly, conceptual frameworks, while valuable for offering theoretical perspectives, have limitations that may hinder their effectiveness in sports science. One key issue is their tendency toward over-abstraction, which can make them too general or theoretical to translate into practical applications. Additionally, conceptual frameworks often oversimplify complex phenomena, failing to capture the multifactorial and dynamic nature of real-world processes, such as the interplay between training load, recovery, and performance. Another significant challenge is the difficulty of implementing theoretical models in practice. Without clear guidance on how to operationalize these frameworks, their usefulness to practitioners may be limited.

In the context of sports science, these limitations emphasize the need to integrate narrative reviews and conceptual frameworks with rigorous methodologies, such as systematic reviews, meta-analyses, and empirical studies. Combining theoretical insights with robust evidence can help bridge the gap between theory and practice, fostering advancements in both understanding and application.

5.3 Practical application

Machine learning (ML) represents an advanced analytic approach in soccer for managing training load and recovery, offering advanced capabilities to analyse complex datasets and provide actionable insights. By processing large volumes of data from external load metrics, ML allows for dynamic training load adjustments. These adjustments ensure that players remain within an optimal load zone, avoiding overreaching or undertraining while mitigate injury risk. ML also excels in identifying non-linear relationships between training load and training outcomes, helping practitioners pinpoint the precise load ranges, targeted according to MD type, while also providing a detailed analysis of drills and playing positions. This allows to maximize performance while minimizing fatigue or injury risks.

The analysis conducted in the first study (Chapter 3) provides valuable insights into the role-specific model of player performance. Specifically, it enables the characterization of players' performance during matches and facilitates comparisons with training exercises across different playing positions. By utilizing external load (EL) data, this study generates specific player profiles that describe match demands, offering practitioners a framework to better understand and manage the workloads experienced during training drills.

This approach allows for the extraction of key information from training exercises, including the primary target of each drill (e.g., neuromuscular or metabolic stimuli) and its intensity. These insights are derived from EL indicators, player density on the pitch, and the type of drills performed. As a result, practitioners can assess whether a particular drill imposes a greater intensity than official matches, while accounting for the specific playing position of each athlete. This understanding enhances the ability to design and optimize training programs tailored to individual roles and positional demands. In this way, practitioners could select with more appropriateness the type of task during the scheduling microcycle process based on the suggestions provided by the proposed machine learning model.

Another impactful study reported within the chapter 3 employs a machine learning approach to provide valuable insights into training and match loads, player performance, and positional demands within the microcycle structure (i.e., MD system). Two computed scores, derived from external load (EL) and internal load (IL) data, were used to describe player workloads and physical performance during training and matches.

By integrating EL and IL indicators, this approach enables practitioners to identify and compare workloads across training drills, official matches, and MDs, while accounting for positional differences. Principal component analysis (PCA) was used to select EL indicators objectively, offering a more robust alternative to subjective methods. These insights allow practitioners to tailor training drills within the microcycle to align with performance goals and the demands of specific matches or player roles, enhancing the precision of training prescription.

One of the most impactful applications of ML lies in injury risk prediction. By integrating training load data with historical injury records, ML can uncover patterns that indicate elevated injury probabilities. For instance, it can identify thresholds of high-speed running or sprinting volume associated with a higher likelihood of soft tissue injuries. Moreover, ML enables a more personalized approach to injury prevention by analyzing individual responses to training loads and accounting for variables such as playing position, age, and previous injury history. This personalized profiling helps tailor load management strategies to individual player needs.

Recovery, a critical aspect of performance and injury prevention, can also be enhanced using ML. By combining recovery metrics such as TQR scale, player's availability and training load metrics, ML can predict a player's readiness for subsequent training sessions or matches. It can analyze how specific training loads affect recovery patterns and provide recommendations for optimizing recovery strategies. Additionally, ML can detect signs of cumulative fatigue by synthesizing data from wearable devices and subjective wellness assessments, allowing for timely

interventions to adjust training loads and prevent chronic fatigue. The integration of training load and recovery data through ML offers further insights, enabling the optimization of training periodization. ML can analyze how these factors interact across microcycles and macrocycles, ensuring that players are adequately prepared for high-intensity matches without risking overtraining or under-recovery. Recovery-based load prescriptions, which adapt training intensity to a player's recovery status, are another area where ML provides significant advantages. This ensures that players who are less recovered can engage in lower-intensity sessions while others maintain higher workloads, facilitating individualized training.

In conclusion, ML is revolutionizing the understanding of training load and recovery in soccer. Its ability to process and analyze complex, multidimensional data provides unparalleled insights into player readiness, injury risk, and performance optimization. By incorporating ML into training strategies, practitioners can enhance decision-making processes, reduce injury risks, and ensure sustainable performance for both individual players and teams.

References

1. Buchheit M, Settembre M, Hader K, McHugh D. Planning the microcycle in elite football: to rest or not to rest? Injuries and days off-feet in elite football.
2. Gabbett TJ, Nassis GP, Oetter E, Pretorius J, Johnston N, Medina D, et al. The athlete monitoring cycle: a practical guide to interpreting and applying training monitoring data. *British journal of sports medicine*. 2017;51(20):1451-2.
3. Gabbett TJ, Ullah S. Relationship between running loads and soft-tissue injury in elite team sport athletes. *J Strength Cond Res*. 2012;26(4):953-60.
4. Impellizzeri FM, Marcora SM, Coutts AJ. Internal and External Training Load: 15 Years On. *Int J Sports Physiol Perform*. 2019;14(2):270-3.
5. Kalkhoven JT, Watsford ML, Coutts AJ, Edwards WB, Impellizzeri FM. Training load and injury: causal pathways and future directions. *Sports Medicine*. 2021;51:1137-50.
6. Pillitteri G, Clemente FM, Sarmento H, Figueiredo A, Rossi A, Bongiovanni T, et al. Translating player monitoring into training prescriptions: Real world soccer scenario and practical proposals. *International Journal of Sports Science & Coaching*. 2024;17479541241289080.
7. Buchheit M, Douchet T, Settembre M, Mchugh D, Hader K, Verheijen R. The 11 Evidence-Informed and Inferred Principles of Microcycle Periodization in Elite Football. *Sport Perform Sci Rep*. 2024;218.
8. Buchheit M, Laursen PB. High-intensity interval training, solutions to the programming puzzle. Part II: anaerobic energy, neuromuscular load and practical applications. *Sports medicine (Auckland, NZ)*. 2013;43(10):927-54.
9. Buchheit M, Laursen PB. High-intensity interval training, solutions to the programming puzzle: Part I: cardiopulmonary emphasis. *Sports medicine (Auckland, NZ)*. 2013;43(5):313-38.
10. Rossi A, Pappalardo L, Cintia P. A narrative review for a machine learning application in sports: an example based on injury forecasting in soccer. *Sports*. 2021;10(1):5.
11. Beato M, Jaward MH, Nassis GP, Figueiredo P, Clemente FM, Krstrup P. An educational review on machine learning: a SWOT analysis for implementing machine learning techniques in football. *International journal of sports physiology and performance*. 2024;1(aop):1-9.

12. Rossi A, Pappalardo L, Cintia P, Iaia FM, Fernández J, Medina D. Effective injury forecasting in soccer with GPS training data and machine learning. *PloS one*. 2018;13(7):e0201264.
13. Rossi A, Pappalardo L, Cintia PJS. A narrative review for a machine learning application in sports: an example based on injury forecasting in soccer. 2022;10(1):5.
14. Pillitteri G, Petrigna L, Ficarra S, Giustino V, Thomas E, Rossi A, et al. Relationship between external and internal load indicators and injury using machine learning in professional soccer: a systematic review and meta-analysis. *Research in sports medicine*. 2024:1-37.
15. Rossi A, Perri E, Pappalardo L, Cintia P, Alberti G, Norman D, et al. Wellness Forecasting by External and Internal Workloads in Elite Soccer Players: A Machine Learning Approach. 2022;13.
16. Rossi A, Perri E, Pappalardo L, Cintia P, Iaia FM. Relationship between External and Internal Workloads in Elite Soccer Players: Comparison between Rate of Perceived Exertion and Training Load. *Applied Sciences*. 2019;9(23):5174.
17. Jeffries AC, Marcora SM, Coutts AJ, Wallace L, McCall A, Impellizzeri FMJSM. Development of a revised conceptual framework of physical training for use in research and practice. 2021:1-16.
18. Bourdon PC, Cardinale M, Murray A, Gatin P, Kellmann M, Varley MC, et al. Monitoring Athlete Training Loads: Consensus Statement. *International journal of sports physiology and performance*. 2017;12(Suppl 2):S2161-s70.
19. Brink MS, Nederhof E, Visscher C, Schmikli SL, Lemmink KA. Monitoring load, recovery, and performance in young elite soccer players. *Journal of strength and conditioning research*. 2010;24(3):597-603.
20. Casamichana D, Castellano J, Calleja-Gonzalez J, San Román J, Castagna CJTJoS, Research C. Relationship between indicators of training load in soccer players. 2013;27(2):369-74.
21. Jaspers A, Brink MS, Probst SG, Frencken WG, Helsen WFJSm. Relationships between training load indicators and training outcomes in professional soccer. 2017;47(3):533-44.
22. McLaren SJ, Macpherson TW, Coutts AJ, Hurst C, Spears IR, Weston MJSm. The relationships between internal and external measures of training load and intensity in team sports: a meta-analysis. 2018;48(3):641-58.
23. Vallance E, Sutton-Charani N, Imoussaten A, Montmain J, Perrey SJAS. Combining internal-and external-training-loads to predict non-contact injuries in soccer. 2020;10(15):5261.
24. Impellizzeri FM, Rampinini E, Marcora SMJJoss. Physiological assessment of aerobic training in soccer. 2005;23(6):583-92.
25. Viru A, Viru MJE, science s. Nature of training effects. 2000;6795.
26. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports medicine (Auckland, NZ)*. 2014;44 Suppl 2(Suppl 2):S139-47.
27. Verstappen S, van Rijn RM, Cost R, Stubbe JH. The Association Between Training Load and Injury Risk in Elite Youth Soccer Players: a Systematic Review and Best Evidence Synthesis. *Sports medicine - open*. 2021;7(1):6.
28. Jeffries AC, Wallace L, Coutts AJ, McLaren SJ, McCall A, Impellizzeri FM. Athlete-Reported Outcome Measures for Monitoring Training Responses: A Systematic Review of Risk of Bias and Measurement Property Quality According to the COSMIN Guidelines. *Int J Sports Physiol Perform*. 2020:1-13.
29. Banister EW, Calvert TW, Savage MV, Bach TJAJS. A systems model of training for athletic performance. 1975;7(3):57-61.
30. Impellizzeri FM, Marcora SM, Coutts AJIjosp, performance. Internal and external training load: 15 years on. 2019;14(2):270-3.
31. Clemente FM, Nikolaidis PT, Rosemann T, Knechtle B. Dose-Response Relationship Between External Load Variables, Body Composition, and Fitness Variables in Professional Soccer Players. *Frontiers in physiology*. 2019;10:443.
32. Pillitteri G, Clemente FM, Petrucci M, Rossi A, Bellafiore M, Bianco A, et al. Toward a New Conceptual Approach to "Intensity" in Soccer Player's Monitoring: A Narrative Review. *Journal of strength and conditioning research*. 2023;37(9):1896-911.
33. Buchheit M, Laursen PBJSm. High-intensity interval training, solutions to the programming puzzle. 2013;43(5):313-38.

34. De Vet HC, Terwee CB, Mokkink LB, Knol DL. Measurement in medicine: a practical guide: Cambridge university press; 2011.
35. Camp WJJoVER. Formulating and evaluating theoretical frameworks for career and technical education research. 2001;26(1):4-25.
36. Rago V, Brito J, Figueiredo P, Costa J, Krstrup P, Rebelo A. Internal training load monitoring in professional football: a systematic review of methods using rating of perceived exertion. The Journal of sports medicine and physical fitness. 2020;60(1):160-71.
37. Buchheit MJMJ. The 30–15 intermittent fitness test: 10 year review. 2010;1(9):278.
38. Miguel M, Oliveira R, Loureiro N, García-Rubio J, Ibáñez SJJJoER, Health P. Load measures in training/match monitoring in soccer: A systematic review. 2021;18(5):2721.
39. Rago V, Brito J, Figueiredo P, Costa J, Barreira D, Krstrup P, et al. Methods to collect and interpret external training load using microtechnology incorporating GPS in professional football: A systematic review. 2020;28(3):437-58.
40. Bhattacharjee A. Social science research: Principles, methods, and practices. 2012.
41. Beato M, Madsen EE, Clubb J, Emmonds S, Krstrup P. Monitoring Readiness to Train and Perform in Female Football: Current Evidence and Recommendations for Practitioners. International journal of sports physiology and performance. 2024;19(3):223-31.
42. Perl JJEJoSS. PerPot: A metamodel for simulation of load performance interaction. 2001;1(2):1-13.
43. Thomas K, Brownstein C, Dent J, Parker P, Goodall S, Howatson GJM, et al. Neuromuscular fatigue and recovery after heavy resistance, jump, and sprint training. 2018;50(12):2526-35.
44. Portenga ST, Aoyagi MW, Cohen AB. Helping to build a profession: A working definition of sport and performance psychology. Journal of Sport Psychology in Action. 2017;8(1):47-59.
45. Drust B, Atkinson G, Reilly TJSm. Future perspectives in the evaluation of the physiological demands of soccer. 2007;37(9):783-805.
46. Helgerud J, Engen LC, Wisloff U, Hoff JJM, sports si, exercise. Aerobic endurance training improves soccer performance. 2001;33(11):1925-31.
47. Aquino R, Carling C, Vieira LHP, Martins G, Jabor G, Machado J, et al. Influence of situational variables, team formation, and playing position on match running performance and social network analysis in brazilian professional soccer players. 2020;34(3):808-17.
48. Gregson W, Drust B, Atkinson G, Salvo VJljosm. Match-to-match variability of high-speed activities in premier league soccer. 2010;31(04):237-42.
49. Mohr M, Krstrup P, Bangsbo JJoSS. Match performance of high-standard soccer players with special reference to development of fatigue. 2003;21(7):519-28.
50. Selmi O, Ouergui I, Levitt DE, Nikolaidis PT, Knechtle B, Bouassida AJOAJoS. Small-sided games are more enjoyable than high-intensity interval training of similar exercise intensity in soccer. 2020;11:77.
51. Trewin J, Meylan C, Varley MC, Cronin JJS, Football Mi. The influence of situational and environmental factors on match-running in soccer: a systematic review. 2017;1(2):183-94.
52. Schamphoeleer E, Roelands B. Mental Fatigue in Sport—From Impaired Performance to Increased Injury Risk. International journal of sports physiology and performance. 2024;19(10):1158-66.
53. Chmura P, Konefał M, Chmura J, Kowalczyk E, Zajac T, Rokita A, et al. Match outcome and running performance in different intensity ranges among elite soccer players. 2018;35(2):197.
54. Clemente F, Aquino R, Praça GM, Rico-González M, Oliveira R, Silva AF, et al. Variability of internal and external loads and technical/tactical outcomes during small-sided soccer games: a systematic review. 2019;39(3):647-72.
55. Impellizzeri FM, Marcora S, Castagna C, Reilly T, Sassi A, Iaia F, et al. Physiological and performance effects of generic versus specific aerobic training in soccer players. 2006;27(06):483-92.
56. Abt G, Lovell RJJoSS. The use of individualized speed and intensity thresholds for determining the distance run at high-intensity in professional soccer. 2009;27(9):893-8.
57. McLaren SJ, Macpherson TW, Coutts AJ, Hurst C, Spears IR, Weston M. The Relationships Between Internal and External Measures of Training Load and Intensity in Team Sports: A Meta-Analysis. Sports medicine (Auckland, NZ). 2018;48(3):641-58.
58. Bangsbo J, Iaia FM, Krstrup PJSm. The Yo-Yo intermittent recovery test. 2008;38(1):37-51.

59. Beato M, Drust B, Iacono AD. Implementing high-speed running and sprinting training in professional soccer. *International journal of sports medicine*. 2021;42(04):295-9.
60. Bangsbo J, Mohr M, Krstrup PJ. Physical and metabolic demands of training and match-play in the elite football player. 2006;24(07):665-74.
61. Stølen T, Chamari K, Castagna C, Wisløff U. Physiology of soccer: an update. *Sports medicine (Auckland, NZ)*. 2005;35(6):501-36.
62. Harper DJ, Carling C, Kiely JJ. High-intensity acceleration and deceleration demands in elite team sports competitive match play: a systematic review and meta-analysis of observational studies. 2019;49(12):1923-47.
63. Mackenzie R, Cushion CJ. Performance analysis in football: A critical review and implications for future research. 2013;31(6):639-76.
64. Rico-González M, Oliveira R, Vieira LHP, Pino-Ortega J, Clemente FJ. Players' performance during worst-case scenarios in professional soccer matches: a systematic review. 2022;39(3):695-713.
65. Sarmiento H, Marcelino R, Anguera MT, Campaniço J, Matos N, Leitão JC. Match analysis in football: a systematic review. 2014;32(20):1831-43.
66. Delves RJ, Aughey RJ, Ball K, Duthie GM. The quantification of acceleration events in elite team sport: a systematic review. 2021;7(1):1-35.
67. Gualtieri A, Rampinini E, Dello Iacono A, Beato M. High-speed running and sprinting in professional adult soccer: current thresholds definition, match demands and training strategies. A systematic review. *Frontiers in Sports and Active Living*. 2023;5:1116293.
68. Di Prampero P, Fusi S, Sepulcri L, Morin J-B, Belli A, Antonutto G. Sprint running: a new energetic approach. 2005;208(14):2809-16.
69. Åstrand I, Åstrand PO, Christensen EH, Hedman RJ. Intermittent muscular work. 1960;48(3-4):448-53.
70. Osgnach C, Poser S, Bernardini R, Rinaldo R, Di Prampero P. Energy cost and metabolic power in elite soccer: a new match analysis approach. 2010;42(1):170-8.
71. Svensson M, Drust B. Testing soccer players. 2005;23(6):601-18.
72. Ulupinar S, Özbay S, Gençoğlu C, Hazır T. Low-to-Moderate Correlations Between Repeated Sprint Ability and Aerobic Capacity: A Systematic Review and Meta-analysis. *Strength & Conditioning Journal*. 2023;45(4).
73. Hostrup M, Bangsbo J. Performance adaptations to intensified training in top-level football. *Sports Medicine*. 2023;53(3):577-94.
74. Oliva-Lozano JM, Muyor JM, Fortes V, McLaren SJ. Decomposing the variability of match physical performance in professional soccer: implications for monitoring individuals. 2021;21(11):1588-96.
75. Carling C, Bradley P, McCall A, Dupont G. Match-to-match variability in high-speed running activity in a professional soccer team. 2016;34(24):2215-23.
76. Pillitteri G, Giustino V, Petrucci M, Rossi A, Bellafiore M, Thomas E, et al. External load profile during different sport-specific activities in semi-professional soccer players. *BMC sports science, medicine & rehabilitation*. 2023;15(1):22.
77. Pillitteri G, Giustino V, Messina G, Petrucci M, Rossi A, Bellafiore M, et al. Comparison of external load indicators between official matches and sport-specific training in semi-professional soccer players: focus on intensity and strength. *The Journal of sports medicine and physical fitness*. 2023;63(3):385-93.
78. Oliveira R, Brito JP, Moreno-Villanueva A, Nalha M, Rico-González M, Clemente FM, editors. Reference Values for External and Internal Training Intensity Monitoring in Young Male Soccer Players: A Systematic Review. *Healthcare*; 2021: Multidisciplinary Digital Publishing Institute.
79. Buchheit M, Settembre M, Hader K, McHugh D. From High-Speed Running to Hobbled on Crutches: A Machine Learning Perspective on the Relationships Between Training Doses and Match Injury Trends. *Sport Perform Sci Rep*. 2023;216:1-11.
80. Kalkhoven JT, Lukauskis-Carvajal M, Sides DL, McLean BD, Watsford ML. A Conceptual Exploration of Hamstring Muscle–Tendon Functioning during the Late-Swing Phase of Sprinting: The Importance of Evidence-Based Hamstring Training Frameworks. *Sports Medicine*. 2023;53(12):2321-46.

81. Gualtieri A, Vicens-Bordas J, Rampinini E, Bravo DF, Beato M. Three-, Four-, and Five-Day Microcycles: The Normality in Professional Football. *International journal of sports physiology and performance*. 2024;19(10):987-95.
82. Haddad M, Stylianides G, Djaoui L, Dellal A, Chamari KJFin. Session-RPE method for training load monitoring: validity, ecological usefulness, and influencing factors. 2017;11:612.
83. Akubat I, Barrett S, Sagarra ML, Abt GJS. The validity of external: internal training load ratios in rested and fatigued soccer players. 2018;6(2):44.
84. Coppalle S, Rave G, Ben Abderrahman A, Ali A, Salhi I, Zouita S, et al. Relationship of pre-season training load with in-season biochemical markers, injuries and performance in professional soccer players. 2019:409.
85. Gaudino P, Iaia FM, Strudwick AJ, Hawkins RD, Alberti G, Atkinson G, et al. Factors influencing perception of effort (session rating of perceived exertion) during elite soccer training. *International journal of sports physiology and performance*. 2015;10(7):860-4.
86. Grünbichler J, Federolf P, Gatterer HJEJoSS. Workload efficiency as a new tool to describe external and internal competitive match load of a professional soccer team: A descriptive study on the relationship between pre-game training loads and relative match load. 2020;20(8):1034-41.
87. Pillitteri G, Rossi A, Bongiovanni T, Puleo G, Petrucci M, Iaia FM, et al. Elite Soccer Players' Weekly Workload Assessment Through a New Training Load and Performance Score. *Research Quarterly for Exercise and Sport*. 2024:1-9.
88. Coyne JO, Coutts AJ, Newton RU, Haff GG. The current state of subjective training load monitoring: follow-up and future directions. *Sports Medicine-Open*. 2022;8(1):53.
89. Coyne JO, Gregory Haff G, Coutts AJ, Newton RU, Nimphius S. The current state of subjective training load monitoring—a practical perspective and call to action. *Sports medicine-open*. 2018;4:1-10.
90. Akubat I, Barrett S, Abt GJljosp, performance. Integrating the internal and external training loads in soccer. 2014;9(3):457-62.
91. Caspersen CJ, Powell KE, Christenson GMJPhr. Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research. 1985;100(2):126.
92. Medicine ACoS. ACSM's guidelines for exercise testing and prescription: Lippincott williams & wilkins; 2013.
93. Nédélec M, McCall A, Carling C, Legall F, Berthoin S, Dupont GJSm. Recovery in soccer. 2012;42(12):997-1015.
94. Pate RRJTp, sportsmedicine. A new definition of youth fitness. 1983;11(4):77-83.
95. Rabbani A, Clemente FM, Kargarfard M, Chamari K. Match Fatigue Time-Course Assessment Over Four Days: Usefulness of the Hooper Index and Heart Rate Variability in Professional Soccer Players. *Frontiers in physiology*. 2019;10:109.
96. McLean BD, Coutts AJ, Kelly V, McGuigan MR, Cormack SJ. Neuromuscular, endocrine, and perceptual fatigue responses during different length between-match microcycles in professional rugby league players. *International journal of sports physiology and performance*. 2010;5(3):367-83.
97. Rossi A, Perri E, Pappalardo L, Cintia P, Alberti G, Norman D, et al. Wellness Forecasting by External and Internal Workloads in Elite Soccer Players: A Machine Learning Approach. 2022:1179.
98. Selmi O, Ouergui I, Muscella A, My G, Marsigliante S, Nobari H, et al. Monitoring Psychometric States of Recovery to Improve Performance in Soccer Players: A Brief Review. 2022;19(15):9385.
99. Kellmann M, Beckmann JJli. Sport, recovery, and performance. 2018.
100. Clemente FM, Silva R, Chen Y-S, Aquino R, Praça GM, Castellano J, et al. Accelerometry-workload indices concerning different levels of participation during congested fixture periods in professional soccer: a pilot study conducted over a full season. 2021;18(3):1137.
101. Nobari H, Alves AR, Haghighi H, Clemente FM, Carlos-Vivas J, Pérez-Gómez J, et al. Association between training load and well-being measures in young soccer players during a season. 2021;18(9):4451.
102. Duignan C, Doherty C, Caulfield B, Blake CJJoat. Single-item self-report measures of team-sport athlete wellbeing and their relationship with training load: A systematic review. 2020;55(9):944-53.
103. Moalla W, Fessi MS, Farhat F, Nouira S, Wong DP, Dupont GJRiSM. Relationship between daily training load and psychometric status of professional soccer players. 2016;24(4):387-94.

104. Pillitteri G, Rossi A, Simonelli C, Leale I, Giustino V, Battaglia G. Association between internal load responses and recovery ability in U19 professional soccer players: A machine learning approach. *Heliyon*. 2023;9(4).
105. Rossi A, Perri E, Pappalardo L, Cintia P, Iaia FMJAS. Relationship between external and internal workloads in elite soccer players: comparison between rate of perceived exertion and training load. 2019;9(23):5174.
106. Rossi A, Pappalardo L, Cintia P, Iaia FM, Fernández J, Medina DJPo. Effective injury forecasting in soccer with GPS training data and machine learning. 2018;13(7):e0201264.
107. Rojas-Valverde D, Pino-Ortega J, Gómez-Carmona CD, Rico-González MJJoER, Health P. A systematic review of methods and criteria standard proposal for the use of principal component analysis in team's sports science. 2020;17(23):8712.
108. Coutts AJ, Crowcroft S, Kempton T. Developing athlete monitoring systems: theoretical basis and practical applications. *Recovery and Well-being in Sport and Exercise: Routledge*; 2021. p. 17-31.
109. Ryan S, Kempton T, Impellizzeri FM, Coutts AJJS, Football Mi. Training monitoring in professional Australian football: theoretical basis and recommendations for coaches and scientists. 2020;4(1):52-8.
110. Edwards RHJBoe. Biochemical bases of fatigue in exercise performance: catastrophe theory of muscular fatigue. 1983;13(13):3-28.
111. Pyne DB, Martin DT. *Fatigue-Insights from individual and team sports. Regulation of fatigue in exercise: Nova Publishers*; 2011. p. 177-86.
112. Enoka RM, Duchateau JJM, sports si, exercise. Translating fatigue to human performance. 2016;48(11):2228.
113. Fuller CW, Ekstrand J, Junge A, Andersen TE, Bahr R, Dvorak J, et al. Consensus statement on injury definitions and data collection procedures in studies of football (soccer) injuries. 2006;16(2):83-92.
114. Waldén M, Mountjoy M, McCall A, Serner A, Massey A, Tol JL, et al. Football-specific extension of the IOC consensus statement: methods for recording and reporting of epidemiological data on injury and illness in sport 2020. 2023.
115. Ekstrand J, Hägglund M, Waldén MJBjasm. Injury incidence and injury patterns in professional football: the UEFA injury study. 2011;45(7):553-8.
116. Ekstrand J, Waldén M, Hägglund MJBjasm. Hamstring injuries have increased by 4% annually in men's professional football, since 2001: a 13-year longitudinal analysis of the UEFA Elite Club injury study. 2016;50(12):731-7.
117. Eckard TG, Padua DA, Hearn DW, Pexa BS, Frank BSJSm. The relationship between training load and injury in athletes: a systematic review. 2018;48(8):1929-61.
118. Ekstrand J, Hägglund M, Waldén MJTAjasm. Epidemiology of muscle injuries in professional football (soccer). 2011;39(6):1226-32.
119. Faude O, Rößler R, Junge AJSm. Football injuries in children and adolescent players: are there clues for prevention? 2013;43(9):819-37.
120. Hägglund M, Waldén M, Magnusson H, Kristenson K, Bengtsson H, Ekstrand JJBjasm. Injuries affect team performance negatively in professional football: an 11-year follow-up of the UEFA Champions League injury study. 2013;47(12):738-42.
121. López-Valenciano A, Ruiz-Pérez I, Garcia-Gómez A, Vera-Garcia FJ, Croix MDS, Myer GD, et al. Epidemiology of injuries in professional football: a systematic review and meta-analysis. 2020;54(12):711-8.
122. Szymiski D, Krutsch V, Achenbach L, Gerling S, Pfeifer C, Alt V, et al. Epidemiological analysis of injury occurrence and current prevention strategies on international amateur football level during the UEFA Regions Cup 2019. 2022;142(2):271-80.
123. Hägglund M, Waldén M, Ekstrand JJSjom, sports si. Injury incidence and distribution in elite football—a prospective study of the Danish and the Swedish top divisions. 2005;15(1):21-8.
124. Klein C, Henke T, Platen PJGJoE, Research S. Injuries in football (soccer)—a systematic review of epidemiology and aetiological aspects. 2018;48(3):309-22.
125. Waldén M, Hägglund M, Magnusson H, Ekstrand JJBjasm. ACL injuries in men's professional football: a 15-year prospective study on time trends and return-to-play rates reveals only 65% of players still play at the top level 3 years after ACL rupture. 2016;50(12):744-50.

126. Della Villa F, Hägglund M, Della Villa S, Ekstrand J, Waldén M. High rate of second ACL injury following ACL reconstruction in male professional footballers: an updated longitudinal analysis from 118 players in the UEFA Elite Club Injury Study. *British journal of sports medicine*. 2021;55(23):1350-6.
127. Pulici L, Certa D, Zago M, Volpi P, Esposito FJCJoSM. Injury Burden in Professional European Football (Soccer): Systematic Review, Meta-Analysis, and Economic Considerations. 2022;10.1097.
128. Ekstrand J. Keeping your top players on the pitch: the key to football medicine at a professional level. BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine; 2013.
129. Bahr R, Krosshaug TJBjasm. Understanding injury mechanisms: a key component of preventing injuries in sport. 2005;39(6):324-9.
130. Meeuwisse WH, Tyreman H, Hagel B, Emery CJCjasm. A dynamic model of etiology in sport injury: the recursive nature of risk and causation. 2007;17(3):215-9.
131. Meeuwisse WHJCJoSM. Assessing causation in sport injury: a multifactorial model. *LWW*; 1994. p. 166-70.
132. Impellizzeri FM, Menaspà P, Coutts AJ, Kalkhoven J, Menaspà MJJJJoat. Training load and its role in injury prevention, part I: back to the future. 2020;55(9):885-92.
133. Snijders C, Matzat U, Reips U-D. "Big Data": big gaps of knowledge in the field of internet science. *International journal of internet science*. 2012;7(1):1-5.
134. Hashem IAT, Yaqoob I, Anuar NB, Mokhtar S, Gani A, Khan SU. The rise of "big data" on cloud computing: Review and open research issues. *Information systems*. 2015;47:98-115.
135. Hey T, Tansley S, Tolle KM. The fourth paradigm: data-intensive scientific discovery: Microsoft research Redmond, WA; 2009.
136. Choi M. Book Review: Data Smart: Using Data Science to Transform Information into Insight. *Healthcare Informatics Research*. 2014;20(3):243-4.
137. Flach P. Machine learning: the art and science of algorithms that make sense of data: Cambridge university press; 2012.
138. Leckey C, van Dyk N, Doherty C, Lawlor A, Delahunt E. Machine learning approaches to injury risk prediction in sport: a scoping review with evidence synthesis. *British Journal of Sports Medicine*. 2024.
139. Claudino JG, Cardoso Filho CA, Boulosa D, Lima-Alves A, Carrion GR, Gianoni RLdS, et al. The role of veracity on the load monitoring of professional soccer players: a systematic review in the face of the big data era. 2021;11(14):6479.
140. Claudino JG, Capanema DdO, de Souza TV, Serrão JC, Machado Pereira AC, Nassis GPJSm-o. Current approaches to the use of artificial intelligence for injury risk assessment and performance prediction in team sports: a systematic review. 2019;5(1):1-12.
141. Majumdar A, Bakirov R, Hodges D, Scott S, Rees TJSM-O. Machine Learning for Understanding and Predicting Injuries in Football. 2022;8(1):1-10.
142. Rico-González M, Pino-Ortega J, Méndez A, Clemente F, Baca AJBoS. Machine learning application in soccer: A systematic review. 2022;40(1):249-63.
143. Oliver JL, Ayala F, Croix MBDS, Lloyd RS, Myer GD, Read PJJJos, et al. Using machine learning to improve our understanding of injury risk and prediction in elite male youth football players. 2020;23(11):1044-8.
144. Dolci F, Hart NH, Kilding AE, Chivers P, Piggott B, Spiteri TJS, et al. Physical and energetic demand of soccer: a brief review. 2020;42(3):70-7.
145. Rampinini E, Coutts AJ, Castagna C, Sassi R, Impellizzeri FJJjasm. Variation in top level soccer match performance. 2007;28(12):1018-24.
146. Osgnach C, Poser S, Bernardini R, Rinaldo R, di Prampero PE. Energy cost and metabolic power in elite soccer: a new match analysis approach. *Medicine and science in sports and exercise*. 2010;42(1):170-8.
147. Al Haddad H, Méndez-Villanueva A, Torreño N, Munguía-Izquierdo D, Suárez-Arrones L. Variability of GPS-derived running performance during official matches in elite professional soccer players. *The Journal of sports medicine and physical fitness*. 2018;58(10):1439-45.
148. Brito Â, Roriz P, Duarte R, Garganta JJJoPAiS. Match-running performance of young soccer players in different game formats. 2018;18(3):410-22.

149. Bloomfield J, Polman R, O'Donoghue P. Physical Demands of Different Positions in FA Premier League Soccer. *Journal of sports science & medicine*. 2007;6(1):63-70.
150. Andrzejewski M, Konefał M, Chmura P, Kowalczyk E, Chmura JJJJoPAiS. Match outcome and distances covered at various speeds in match play by elite German soccer players. 2016;16(3):817-28.
151. Di Salvo V, Gregson W, Atkinson G, Tordoff P, Drust B. Analysis of high intensity activity in Premier League soccer. *International journal of sports medicine*. 2009;30(3):205-12.
152. Bush M, Barnes C, Archer DT, Hogg B, Bradley PSJHms. Evolution of match performance parameters for various playing positions in the English Premier League. 2015;39:1-11.
153. Di Salvo V, Gregson W, Atkinson G, Tordoff P, Drust BJJosm. Analysis of high intensity activity in Premier League soccer. 2009;30(03):205-12.
154. Schwellnus M, Soligard T, Alonso JM, Bahr R, Clarsen B, Dijkstra HP, et al. How much is too much? (Part 2) International Olympic Committee consensus statement on load in sport and risk of illness. *British journal of sports medicine*. 2016;50(17):1043-52.
155. Soligard T, Schwellnus M, Alonso JM, Bahr R, Clarsen B, Dijkstra HP, et al. How much is too much? (Part 1) International Olympic Committee consensus statement on load in sport and risk of injury. *Br J Sports Med*. 2016;50(17):1030-41.
156. Bourdon PC, Cardinale M, Murray A, Gustin P, Kellmann M, Varley MC, et al. Monitoring athlete training loads: consensus statement. 2017;12(s2):S2-161-S2-70.
157. Coutts AJ, Crowcroft S, Kempton T. Developing athlete monitoring systems. Sport, recovery, and performance: Interdisciplinary insights. 2017.
158. Impellizzeri FM, Rampinini E, Marcora SM. Physiological assessment of aerobic training in soccer. *Journal of sports sciences*. 2005;23(6):583-92.
159. Vanrenterghem J, Nedergaard NJ, Robinson MA, Drust B. Training load monitoring in team sports: a novel framework separating physiological and biomechanical load-adaptation pathways. *Sports medicine*. 2017;47(11):2135-42.
160. Maughan P, Swinton P, MacFarlane NJJosm. Relationships between training load variables in professional youth football players. 2021;42(07):624-9.
161. Staunton CA, Abt G, Weaving D, Wundersitz DWJJoS, Sport Mi. Misuse of the term 'load' in sport and exercise science. 2021.
162. Impellizzeri FM, Jeffries AC, Weisman A, Coutts AJ, McCall A, McLaren SJ, et al. A Clarification of the (Mis) Use of the Term 'Load' in Sport and Exercise Science: Why It Is Appropriate and Scientific.
163. Coutts AJ, Crowcroft S, Kempton TJR, Sport W-bi, Insights EI. 2 Developing athlete monitoring systems • eoretical basis and practical applications. 2021.
164. Impellizzeri FM, Rampinini E, Coutts AJ, Sassi A, Marcora SMJM, sports Si, et al. Use of RPE-based training load in soccer. 2004;36(6):1042-7.
165. Foster C, Daines E, Hector L, Snyder AC, Welsh RJWmj. Athletic performance in relation to training load. 1996;95(6):370-4.
166. Winter EM, Abt G, Brookes FC, Challis JH, Fowler NE, Knudson DV, et al. Misuse of "power" and other mechanical terms in sport and exercise science research. 2016;30(1):292-300.
167. Knuttgen HGJM, Sports Si. Force, work, power, and exercise. 1978;10(3):227-8.
168. Winter EM, Fowler NJJoss. Exercise defined and quantified according to the Systeme International d'Unites. 2009;27(5):447-60.
169. Seiler SJJSPP. What is best practice for training intensity and duration distribution in endurance athletes. 2010;5(3):276-91.
170. Viru AJJJoSM. The mechanism of training effects: a hypothesis. 1984;5(05):219-27.
171. Smith DJJSm. A framework for understanding the training process leading to elite performance. 2003;33(15):1103-26.
172. Torreño N, Munguía-Izquierdo D, Coutts A, Sáez de Villarreal E, Asian-Clemente J, Suarez-Arrones LJJoSP, et al. Relationship between external and internal loads of professional soccer players during full matches in official games using global positioning systems and heart-rate technology. 2016;11(7).
173. Sandford GN, Laursen PB, Buchheit MJSM. Anaerobic Speed/Power Reserve and Sport Performance: Scientific Basis, Current Applications and Future Directions. 2021;51(10):2017-28.

174. Bok D, Rakovac M, Foster C. An Examination and Critique of Subjective Methods to Determine Exercise Intensity: The Talk Test, Feeling Scale, and Rating of Perceived Exertion. *Sports medicine (Auckland, NZ)*. 2022.
175. Rago V, Brito J, Figueiredo P, Krstrup P, Rebelo A. Relationship between External Load and Perceptual Responses to Training in Professional Football: Effects of Quantification Method. *Sports (Basel, Switzerland)*. 2019;7(3).
176. Alemdaroğlu U. External and internal training load relationships in soccer players. 2020.
177. Wiig H, Andersen TE, Luteberget LS, Spencer M. Individual Response to External Training Load in Elite Football Players. *International journal of sports physiology and performance*. 2020;15(5):696-704.
178. Scott BR, Lockie RG, Knight TJ, Clark AC, Janse de Jonge XA. A comparison of methods to quantify the in-season training load of professional soccer players. *Int J Sports Physiol Perform*. 2013;8(2):195-202.
179. Scott TJ, Black CR, Quinn J, Coutts AJ. Validity and reliability of the session-RPE method for quantifying training in Australian football: a comparison of the CR10 and CR100 scales. *Journal of strength and conditioning research*. 2013;27(1):270-6.
180. Maughan PC, MacFarlane NG, Swinton PA. Relationship between subjective and external training load variables in youth soccer players. 2021;16(8):1127-33.
181. Laursen PB, Jenkins DG. The scientific basis for high-intensity interval training. 2002;32(1):53-73.
182. Billat LV, Koralsztejn JP. Significance of the velocity at VO₂max and time to exhaustion at this velocity. 1996;22(2):90-108.
183. Billat LV. Interval training for performance: a scientific and empirical practice. 2001;31(1):13-31.
184. Midgley AW, McNaughton LR, Wilkinson MJ. Is there an optimal training intensity for enhancing the maximal oxygen uptake of distance runners? 2006;36(2):117-32.
185. Gollnick P, Piehl K, Saltin B. Selective glycogen depletion pattern in human muscle fibres after exercise of varying intensity and at varying pedalling rates. 1974;241(1):45-57.
186. Vourimaa T, Vasankari T, Rusko H. Comparison of Physiological Strain and Muscular Performance of Athletes During Two Intermittent Running Exercises at the Velocity Associated with V_{O2}max. 2000;21(02):96-101.
187. Hoff J, Helgerud J. Endurance and strength training for soccer players. 2004;34(3):165-80.
188. Stone MH, Stone M, Sands WA. Principles and practice of resistance training: Human Kinetics; 2007.
189. Gómez-Carmona CD, Gamonal JM, Pino-Ortega J, Ibáñez SJ. Comparative analysis of load profile between small-sided games and official matches in youth soccer players. 2018;6(4):173.
190. Hill-Haas SV, Dawson B, Impellizzeri FM, Coutts AJ. Physiology of small-sided games training in football. 2011;41(3):199-220.
191. Asian-Clemente J, Rabano-Muñoz A, Muñoz B, Franco J, Suarez-Arrones LJ. Can small-side games provide adequate high-speed training in professional soccer? 2021;42(06):523-8.
192. Achten J, Jeukendrup AE. Heart rate monitoring. 2003;33(7):517-38.
193. Mendez-Villanueva A, Buchheit M, Simpson B, Bourdon PC. Match play intensity distribution in youth soccer. *International journal of sports medicine*. 2013;34(2):101-10.
194. Blondel N, Berthoin S, Billat V, Lense G. Relationship between run times to exhaustion at 90, 100, 120, and 140% of v_V O₂max and velocity expressed relatively to critical velocity and maximal velocity. 2001;22(01):27-33.
195. Dellal A, Varliette C, Owen A, Chirico EN, Pialoux V. Small-sided games versus interval training in amateur soccer players: effects on the aerobic capacity and the ability to perform intermittent exercises with changes of direction. 2012;26(10):2712-20.
196. Martín-García A, Díaz AG, Bradley PS, Morera F, Casamichana DJ. Quantification of a professional football team's external load using a microcycle structure. 2018;32(12):3511-8.
197. Derbidge C, Moody JA, Byrne PJ. Can the Use of an External: Internal Ratio During Standardised Small-Sided Games be a Detector of Fatigue in Professional Adolescent Soccer Players? 2020.
198. Lahti J, Mendiguchia J, Ahtiainen J, Anula L, Kononen T, Kujala M, et al. Multifactorial individualised programme for hamstring muscle injury risk reduction in professional football: protocol for a prospective cohort study. 2020;6(1):e000758.

199. Buchheit MJAdH. The 30-15 Intermittent Fitness Test: a new intermittent running field test for intermittent sport players-Part 1. 2005;87:27-34.
200. Angus SDJJoSS. Did recent world record marathon runners employ optimal pacing strategies? 2014;32(1):31-45.
201. Bloomfield J, Polman R, O'Donoghue PJJoss, medicine. Physical demands of different positions in FA Premier League soccer. 2007;6(1):63.
202. Giménez JV, Leicht AS, Gomez MAJJoHK. Physical Performance Differences Between Starter and Non-Starter Players During Professional Soccer Friendly Matches. 2019;69:283.
203. Marynowicz J, Kikut K, Lango M, Horna D, Andrzejewski MJTJoS, Research C. Relationship between the session-rpe and external measures of training load in youth soccer training. 2020;34(10):2800-4.
204. Borg GAJM, sports si, exercise. Psychophysical bases of perceived exertion. 1982.
205. Eickhoff-Shemek JM, Craig ACJAsH, Journal F. Putting the New ACSM's Pre-Activity Health Screening Guidelines Into Practice. 2017;21(3):11-21.
206. Pescatello LS, Riebe D, Thompson PD. ACSM's guidelines for exercise testing and prescription: Lippincott Williams & Wilkins; 2014.
207. Losnegard T, Skarli S, Hansen J, Roterud S, Svendsen IS, Rønnestad BR, et al. Is Rating of Perceived Exertion a Valuable Tool for Monitoring Exercise Intensity During Steady-State Conditions in Elite Endurance Athletes? 2021;16(11):1589-95.
208. Malone S, Owen A, Newton M, Mendes B, Tiernan L, Hughes B, et al. Wellbeing perception and the impact on external training output among elite soccer players. 2018;21(1):29-34.
209. Arrones LS, Torreno N, Requena B, De Villarreal E, Casamichana D, Carlos J, et al. Match-play activity profile in professional soccer players during official games and the relationship between external and internal load. 2014;55:1417-22.
210. Reinhardt L, Schulze S, Schwesig R, Kurz EJJJoSM. Physical Match Performance in Sub-elite Soccer Players—Introduction of a new Index. 2020;41(12):858-66.
211. Montini M, Rocchi JEJJoS, Research C. Monitoring Training Load in Soccer: The ROMEI Model. 2020.
212. Bhattacharjee A. Social science research: Principles, methods, and practices: University of South Florida; 2012.
213. Pillitteri G. FMC, M. Petrucci, A. Rossi, M. Bellafore, A. Bianco, A. Palma, G. Battaglia. Towards a new conceptual approach to “intensity” in soccer player's monitoring: A narrative review. Journal of Strength & Conditioning Research. 2023;In press.
214. Suarez-Arrones L, Torreño N, Requena B, Sáez De Villarreal E, Casamichana D, Barbero-Alvarez JC, et al. Match-play activity profile in professional soccer players during official games and the relationship between external and internal load. J Sports Med Phys Fitness. 2015;55(12):1417-22.
215. Torreño N, Munguía-Izquierdo D, Coutts A, de Villarreal ES, Asian-Clemente J, Suarez-Arrones L. Relationship Between External and Internal Loads of Professional Soccer Players During Full Matches in Official Games Using Global Positioning Systems and Heart-Rate Technology. International journal of sports physiology and performance. 2016;11(7):940-6.
216. Gabbett TJ. The training-injury prevention paradox: should athletes be training smarter and harder? Br J Sports Med. 2016;50(5):273-80.
217. Gabbett TJ, Whiteley RJJjosp, performance. Two training-load paradoxes: can we work harder and smarter, can physical preparation and medical be teammates? 2017;12(Suppl. 2):50-4.
218. Gabbett TJJBjasm. Debunking the myths about training load, injury and performance: empirical evidence, hot topics and recommendations for practitioners. 2020;54(1):58-66.
219. Windt J, Zumbo BD, Sporer B, MacDonald K, Gabbett TJJBjasm. Why do workload spikes cause injuries, and which athletes are at higher risk? Mediators and moderators in workload–injury investigations. BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine; 2017. p. 993-4.
220. Griffin A, Kenny IC, Comyns TM, Lyons MJSM. The association between the acute: chronic workload ratio and injury and its application in team sports: a systematic review. 2020;50(3):561-80.
221. Impellizzeri FM, McCall A, Ward P, Bornn L, Coutts AJJJoat. Training load and its role in injury prevention, part 2: conceptual and methodologic pitfalls. 2020;55(9):893-901.

222. Coyne JOC, Gregory Haff G, Coutts AJ, Newton RU, Nimphius S. The Current State of Subjective Training Load Monitoring-a Practical Perspective and Call to Action. *Sports medicine - open*. 2018;4(1):58.
223. Drew MK, Finch CFJSm. The relationship between training load and injury, illness and soreness: a systematic and literature review. 2016;46(6):861-83.
224. Rago V, Brito J, Figueiredo P, Costa J, Barreira D, Krstrup P, et al. Methods to collect and interpret external training load using microtechnology incorporating GPS in professional football: a systematic review. *Research in Sports Medicine*. 2020;28(3):437-58.
225. Rago V, Brito J, Figueiredo P, Krstrup P, Rebelo A. Application of individualized speed zones to quantify external training load in professional soccer. *Journal of Human Kinetics*. 2020;72(1):279-89.
226. Rago V, Rebelo A, Krstrup P, Mohr M. Contextual Variables and Training Load Throughout a Competitive Period in a Top-Level Male Soccer Team. *J Strength Cond Res*. 2021;35(11):3177-83.
227. Windt J, Gabbett TJJBSm. How do training and competition workloads relate to injury? The workload—injury aetiology model. 2017;51(5):428-35.
228. Buchheit M, Laursen PBJSm. High-intensity interval training, solutions to the programming puzzle: Part I: cardiopulmonary emphasis. 2013;43(5):313-38.
229. Coyne JOC, Coutts AJ, Newton RU, Haff GG. The Current State of Subjective Training Load Monitoring: Follow-Up and Future Directions. *Sports medicine - open*. 2022;8(1):53.
230. Pillitteri G, Clemente FM, Petrucci M, Rossi A, Bellafiore M, Bianco A, et al. Toward a New Conceptual Approach to “Intensity” in Soccer Player's Monitoring: A Narrative Review. *The Journal of Strength & Conditioning Research*. 2023;37(9):1896-911.
231. Foster C. Monitoring training in athletes with reference to overtraining syndrome. *Medicine and science in sports and exercise*. 1998;30(7):1164-8.
232. Hulin BT, Gabbett TJ, Lawson DW, Caputi P, Sampson JA. The acute: chronic workload ratio predicts injury: high chronic workload may decrease injury risk in elite rugby league players. *British journal of sports medicine*. 2016;50(4):231-6.
233. Heart Rate Monitoring in Soccer: Interest and Limits During Competitive Match Play and Training, Practical Application: Erratum. *J Strength Cond Res*. 2022;36(10):e105.
234. Manzi V, Bovenzi A, Franco Impellizzeri M, Carminati I, Castagna C. Individual Training-Load and Aerobic-Fitness Variables in Premiership Soccer Players During the Precompetitive Season. *The Journal of Strength & Conditioning Research*. 2013;27(3):631-6.
235. Gabbett TJ, Whyte DG, Hartwig TB, Wescombe H, Naughton GAJSm. The relationship between workloads, physical performance, injury and illness in adolescent male football players. 2014;44(7):989-1003.
236. Costa JA, Rago V, Brito P, Figueiredo P, Sousa A, Abade E, et al. Training in women soccer players: A systematic review on training load monitoring. 2022:4714.
237. Kenttä G, Hassmén P. Overtraining and recovery. A conceptual model. *Sports Med*. 1998;26(1):1-16.
238. Ravé G, Granacher U, Boullosa D, Hackney AC, Zouhal HJFiP. How to use global positioning systems (gps) data to monitor training load in the “real world” of elite soccer. 2020:944.
239. Ren H, Pan DZ, Alpert CJ, Nam G-J, Villarrubia P, editors. *Hippocrates: First-do-no-harm detailed placement*. 2007 Asia and South Pacific Design Automation Conference; 2007: IEEE.
240. Nassis GP, Brito J, Figueiredo P, Gabbett TJJBSm. Injury prevention training in football: let's bring it to the real world. *BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine*; 2019. p. 1328-9.
241. Impellizzeri FM, Tenan MS, Kempton T, Novak A, Coutts AJIjosp, performance. Acute: chronic workload ratio: conceptual issues and fundamental pitfalls. 2020;15(6):907-13.
242. Renfree A, Casado A, McLaren SJRiSM. Re-thinking athlete training loads: would you rather have one big rock or lots of little rocks dropped on your foot? 2022;30(5):573-6.
243. Foster C, Boullosa D, McGuigan M, Fusco A, Cortis C, Arney BE, et al. 25 years of session rating of perceived exertion: historical perspective and development. *International journal of sports physiology and performance*. 2021;16(5):612-21.
244. Buchheit M, Sandua M, Berndsen J, Shelton A, Smith S, Norman D, et al. Loading patterns and programming practises in elite football: insights from 100 elite practitioners. 2021;153:v1.

245. Gabbett TJ, Ullah SJToS, Research C. Relationship between running loads and soft-tissue injury in elite team sport athletes. 2012;26(4):953-60.
246. Malone S, Owen A, Mendes B, Hughes B, Collins K, Gabbett TJJos, et al. High-speed running and sprinting as an injury risk factor in soccer: Can well-developed physical qualities reduce the risk? 2018;21(3):257-62.
247. Duhig S, Shield AJ, Opar D, Gabbett TJ, Ferguson C, Williams MJBjosc. Effect of high-speed running on hamstring strain injury risk. 2016;50(24):1536-40.
248. Enright K, Green M, Hay G, Malone JJJjosc. Workload and injury in professional soccer players: role of injury tissue type and injury severity. 2020;41(02):89-97.
249. Turner AJS, Journal C. The science and practice of periodization: a brief review. 2011;33(1):34-46.
250. Cissik J, Hedrick A, Barnes MJS, Journal C. Challenges applying the research on periodization. 2008;30(1):45-51.
251. Ehrmann FE, Duncan CS, Sindhusake D, Franzsen WN, Greene DAJTJoS, Research C. GPS and injury prevention in professional soccer. 2016;30(2):360-7.
252. Riboli A, Coratella G, Rampichini S, Cé E, Esposito FJPo. Area per player in small-sided games to replicate the external load and estimated physiological match demands in elite soccer players. 2020;15(9):e0229194.
253. McArdle WD, Katch FI, Katch VL. Exercise physiology: nutrition, energy, and human performance: Lippincott Williams & Wilkins; 2010.
254. Sandage MJ, Pascoe DDJPov, disorders v. Translating exercise science into voice care. 2010;20(3):84-9.
255. Seiler S. What is best practice for training intensity and duration distribution in endurance athletes? International journal of sports physiology and performance. 2010;5(3):276-91.
256. Riboli A, Esposito F, Coratella GJTJoS, Research C. Small-Sided Games in Elite Football: Practical Solutions to Replicate the 4-min Match-Derived Maximal Intensities. 2022;10.1519.
257. Bangsbo J, Iaia FM, Krstrup P. Metabolic response and fatigue in soccer. Int J Sports Physiol Perform. 2007;2(2):111-27.
258. Riboli A, Olthof SB, Esposito F, Coratella GJBos. Training elite youth soccer players: area per player in small-sided games to replicate the match demands. 2022;39(3):579-98.
259. Rampinini E, Impellizzeri FM, Castagna C, Abt G, Chamari K, Sassi A, et al. Factors influencing physiological responses to small-sided soccer games. 2007;25(6):659-66.
260. Clemente FM, Martins FM, Mendes RSJS, Journal C. Periodization based on small-sided soccer games: Theoretical considerations. 2014;36(5):34-43.
261. Dello Iacono A, McLaren SJ, Macpherson TW, Beato M, Weston M, Unnithan VB, et al. Quantifying exposure and intra-individual reliability of high-speed and sprint running during sided-games training in soccer players: a systematic review and meta-analysis. Sports Medicine. 2023;53(2):371-413.
262. Pillitteri G, Rossi A, Cintia P, Trecroci A, Petrucci M, Battaglia G. Association between match-related physical activity profiles and playing positions in different tasks: A data driven approach. Journal of Sports Sciences. 2024;42(5):465-74.
263. Thibault GJNSIA. A graphical model for interval training. 2003;18(3):49-56.
264. Trench MG, Morera FC, Hernández IG, Alcalá EP, Tarragó JR, Garcia AM, et al. Entrenamiento en deportes de equipo: El entrenamiento optimizador en el Fútbol Club Barcelona. 2020;36(142):55-66.
265. Verheijen RJFI. The original guide to football periodization. Part 1. 2014.
266. Buchheit M, Settembre M, Hader K, McHugh D. Exposures to near-to-maximal speed running bouts during different turnarounds in elite football: association with match hamstring injuries. Biology of Sport. 2023;40(4):1057-67.
267. Clemente FM, Rabbani A, Conte D, Castillo D, Afonso J, Truman Clark CC, et al. Training/match external load ratios in professional soccer players: A full-season study. International journal of environmental research and public health. 2019;16(17):3057.
268. Baptista I, Johansen D, Seabra A, Pettersen SA. Position specific player load during match-play in a professional football club. PloS one. 2018;13(5):e0198115.

269. Thornton HR, Delaney JA, Duthie GM, Dascombe BJ. Monitoring athlete performance. Developing athlete monitoring systems in team sports: data analysis and visualization. 2019;14(6):698-705.
270. Beato M, Drust B, Iacono AD. Implementing high-speed running and sprinting training in professional soccer. 2021;42(04):295-9.
271. Clemente F, Pillitteri G, Vieira LHP, Rabbani A, Zmijewski P, Beato M. Balancing the load: A narrative review with methodological implications of compensatory training strategies for non-starting soccer players. *Biology of Sport*. 2024;41(4):173-85.
272. Rago V, Brito J, Figueiredo P, Krstrup P, Rebelo A. Application of Individualized Speed Zones to Quantify External Training Load in Professional Soccer. *J Hum Kinet*. 2020;72:279-89.
273. Delaney JA, Duthie GM, Thornton HR, Pyne DBJS, Football Mi. Quantifying the relationship between internal and external work in team sports: development of a novel training efficiency index. 2018;2(2):149-56.
274. Lazarus BH, Stewart AM, White KM, Rowell AE, Esmaeili A, Hopkins WG, et al. Proposal of a Global Training Load Measure Predicting Match Performance in an Elite Team Sport. *Frontiers in physiology*. 2017;8:930.
275. Pappalardo L, Cintia P, Ferragina P, Massucco E, Pedreschi D, Giannotti F. PlayeRank: data-driven performance evaluation and player ranking in soccer via a machine learning approach. 2019;10(5):1-27.
276. Shushan T, McLaren SJ, Buchheit M, Scott TJ, Barrett S, Lovell R. Submaximal fitness tests in team sports: a theoretical framework for evaluating physiological state. *Sports Medicine*. 2022;52(11):2605-26.
277. Wilmore JH, Costill DL, Kenney WL. *Physiology of sport and exercise: Human kinetics* Champaign, IL; 2004.
278. Ekstrand J, Lundqvist D, Davison M, D'Hooghe M, Pensgaard AM. Communication quality between the medical team and the head coach/manager is associated with injury burden and player availability in elite football clubs. 2019;53(5):304-8.
279. Ekstrand J. Communication quality between the medical team and. 2019.
280. Hader K, Rumpf MC, Hertzog M, Kilduff LP, Girard O, Silva JR. Monitoring the Athlete Match Response: Can External Load Variables Predict Post-match Acute and Residual Fatigue in Soccer? A Systematic Review with Meta-analysis. *Sports medicine - open*. 2019;5(1):48.
281. Viru A, Viru M. Nature of training effects. *Exercise and sport science*. 2000;6795.
282. Jaspers A, Brink MS, Probst SG, Frencken WG, Helsen WF. Relationships Between Training Load Indicators and Training Outcomes in Professional Soccer. *Sports medicine (Auckland, NZ)*. 2017;47(3):533-44.
283. Gabbett TJ, Whyte DG, Hartwig TB, Wescombe H, Naughton GA. The relationship between workloads, physical performance, injury and illness in adolescent male football players. *Sports medicine (Auckland, NZ)*. 2014;44(7):989-1003.
284. Jeffries AC, Marcora SM, Coutts AJ, Wallace L, McCall A, Impellizzeri FM. Development of a Revised Conceptual Framework of Physical Training for Use in Research and Practice. *Sports medicine (Auckland, NZ)*. 2021.
285. Bartlett JD, O'Connor F, Pitchford N, Torres-Ronda L, Robertson SJ. Relationships Between Internal and External Training Load in Team-Sport Athletes: Evidence for an Individualized Approach. *International journal of sports physiology and performance*. 2017;12(2):230-4.
286. Akenhead R, Harley JA, Tweddle SP. Examining the External Training Load of an English Premier League Football Team With Special Reference to Acceleration. *Journal of strength and conditioning research*. 2016;30(9):2424-32.
287. Akubat I, Barrett S, Abt G. Integrating the internal and external training loads in soccer. *International journal of sports physiology and performance*. 2014;9(3):457-62.
288. Beato M, Drust B. Acceleration intensity is an important contributor to the external and internal training load demands of repeated sprint exercises in soccer players. *Research in sports medicine (Print)*. 2021;29(1):67-76.

289. Casamichana D, Castellano J, Calleja-Gonzalez J, San Román J, Castagna C. Relationship between indicators of training load in soccer players. *Journal of strength and conditioning research*. 2013;27(2):369-74.
290. Castagna C, D'Ottavio S, Cappelli S, Araújo Póvoas SC. The Effects of Long Sprint Ability-Oriented Small-Sided Games Using Different Ratios of Players to Pitch Area on Internal and External Load in Soccer Players. *Int J Sports Physiol Perform*. 2019:1265-72.
291. Castillo D, Weston M, McLaren SJ, Cámara J, Yanci J. Relationships Between Internal and External Match-Load Indicators in Soccer Match Officials. *International journal of sports physiology and performance*. 2017;12(7):922-7.
292. Coppalle S, Ravé G, Moran J, Salhi I, Abderrahman AB, Zouita S, et al. Internal and External Training Load in Under-19 versus Professional Soccer Players during the In-Season Period. *International journal of environmental research and public health*. 2021;18(2).
293. Costa EC, Vieira CM, Moreira A, Ugrinowitsch C, Castagna C, Aoki MS. Monitoring external and internal loads of brazilian soccer referees during official matches. *Journal of sports science & medicine*. 2013;12(3):559-64.
294. David C, Julien C. The Relationship Between Intensity Indicators in Small-Sided Soccer Games. *Journal of human kinetics*. 2015;46:119-28.
295. Giménez JV, Leicht AS, Gomez MA. Physical Performance Differences Between Starter and Non-Starter Players During Professional Soccer Friendly Matches. *Journal of human kinetics*. 2019;69:283-91.
296. Malone JJ, Di Michele R, Morgans R, Burgess D, Morton JP, Drust B. Seasonal training-load quantification in elite English premier league soccer players. *International journal of sports physiology and performance*. 2015;10(4):489-97.
297. Martín-López Á, Mendes RS, Castillo-Rodríguez A. Internal and External Loads in Training Week Before the Competition in U19 High-Level Soccer Players. *Journal of strength and conditioning research*. 2021;35(6):1766-72.
298. Oliveira R, Brito J, Martins A, Mendes B, Calvete F, Carriço S, et al. In-season training load quantification of one-, two- and three-game week schedules in a top European professional soccer team. *Physiology & behavior*. 2019;201:146-56.
299. Oliveira R, Brito JP, Martins A, Mendes B, Marinho DA, Ferraz R, et al. In-season internal and external training load quantification of an elite European soccer team. *PloS one*. 2019;14(4):e0209393.
300. Miguel M, Oliveira R, Loureiro N, García-Rubio J, Ibáñez SJ. Load Measures in Training/Match Monitoring in Soccer: A Systematic Review. *International journal of environmental research and public health*. 2021;18(5).
301. Grünbichler J, Federolf P, Gatterer H. Workload efficiency as a new tool to describe external and internal competitive match load of a professional soccer team: A descriptive study on the relationship between pre-game training loads and relative match load. *European journal of sport science*. 2020;20(8):1034-41.
302. Malone S, Owen A, Newton M, Mendes B, Tiernan L, Hughes B, et al. Wellbeing perception and the impact on external training output among elite soccer players. *J Sci Med Sport*. 2018;21(1):29-34.
303. Akubat I, Barrett S, Sagarra ML, Abt G. The Validity of External:Internal Training Load Ratios in Rested and Fatigued Soccer Players. *Sports (Basel, Switzerland)*. 2018;6(2).
304. Clemente FM, Rabbani A, Conte D, Castillo D, Afonso J, Truman Clark CC, et al. Training/Match External Load Ratios in Professional Soccer Players: A Full-Season Study. *International journal of environmental research and public health*. 2019;16(17).
305. Rebelo A, Brito J, Seabra A, Oliveira J, Drust B, Krstrup P. A new tool to measure training load in soccer training and match play. *International journal of sports medicine*. 2012;33(4):297-304.
306. Nobari H, Praça GM, Clemente FM, Pérez-Gómez J, Carlos Vivas J, Ahmadi M. Comparisons of new body load and metabolic power average workload indices between starters and non-starters: A full-season study in professional soccer players. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*. 2020:1754337120974873.
307. Reinhardt L, Schulze S, Schwesig R, Kurz E. Physical Match Performance in Sub-elite Soccer Players - Introduction of a new Index. *International journal of sports medicine*. 2020;41(12):858-66.

308. Claudino JG, Capanema DO, de Souza TV, Serrão JC, Machado Pereira AC, Nassis GP. Current Approaches to the Use of Artificial Intelligence for Injury Risk Assessment and Performance Prediction in Team Sports: a Systematic Review. *Sports medicine - open*. 2019;5(1):28.
309. Van Eetvelde H, Mendonça LD, Ley C, Seil R, Tischer T. Machine learning methods in sport injury prediction and prevention: a systematic review. *J Exp Orthop*. 2021;8(1):27.
310. Rossi A, Pappalardo L, Cintia P, Iaia FM, Fernández J, Medina D. Effective injury forecasting in soccer with GPS training data and machine learning. *PloS one*. 2018;13(7):e0201264.
311. Vallance E, Sutton-Charani N, Imoussaten A, Montmain J, Perrey S. Combining Internal-and External-Training-Loads to Predict Non-Contact Injuries in Soccer. *Applied Sciences*. 2020;10(15):5261.
312. Geurkink Y, Vandewiele G, Lievens M, de Turck F, Ongenae F, Matthys SPJ, et al. Modeling the Prediction of the Session Rating of Perceived Exertion in Soccer: Unraveling the Puzzle of Predictive Indicators. *International journal of sports physiology and performance*. 2019;14(6):841–6.
313. Jaspers A, De Beéck TO, Brink MS, Frencken WGP, Staes F, Davis JJ, et al. Relationships Between the External and Internal Training Load in Professional Soccer: What Can We Learn From Machine Learning? *International journal of sports physiology and performance*. 2018;13(5):625-30.
314. Kotsiantis SB, Zaharakis I, Pintelas P. Supervised machine learning: A review of classification techniques. *Emerging artificial intelligence applications in computer engineering*. 2007;160(1):3-24.
315. Downs SH, Black N. 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*. 1998;52(6):377-84.
316. Kaur M, Ribeiro DC, Theis JC, Webster KE, Sole G. Movement Patterns of the Knee During Gait Following ACL Reconstruction: A Systematic Review and Meta-Analysis. *Sports medicine (Auckland, NZ)*. 2016;46(12):1869-95.
317. Effect Sizes Based on Correlations. *Introduction to Meta-Analysis* 2009. p. 41-3.
318. Enes A, Oneda G, Alves DL, Palumbo DP, Cruz R, Moiano Junior JVM, et al. Determinant Factors of the Match-Based Internal Load in Elite Soccer Players. *Research quarterly for exercise and sport*. 2021;92(1):63-70.
319. Gomez-Piriz PT, Jiménez-Reyes P, Ruiz-Ruiz C. Relation between total body load and session rating of perceived exertion in professional soccer players. *Journal of strength and conditioning research*. 2011;25(8):2100-3.
320. Jaspers A, Kuyvenhoven JP, Staes F, Frencken WGP, Helsen WF, Brink MS. Examination of the external and internal load indicators' association with overuse injuries in professional soccer players. *J Sci Med Sport*. 2018;21(6):579-85.
321. Lacome M, Simpson B, Broad N, Buchheit M. Monitoring Players' Readiness Using Predicted Heart-Rate Responses to Soccer Drills. *International journal of sports physiology and performance*. 2018;13(10):1273-80.
322. Lu D, Howle K, Waterson A, Duncan C, Duffield R. Workload profiles prior to injury in professional soccer players. *Science and Medicine in Football*. 2017;1(3):237-43.
323. Malone S, Owen A, Mendes B, Hughes B, Collins K, Gabbett TJ. High-speed running and sprinting as an injury risk factor in soccer: Can well-developed physical qualities reduce the risk? *J Sci Med Sport*. 2018;21(3):257-62.
324. Marynowicz J, Kikut K, Lango M, Horna D, Andrzejewski M. Relationship Between the Session-RPE and External Measures of Training Load in Youth Soccer Training. *Journal of strength and conditioning research*. 2020;34(10):2800-4.
325. Maughan P, Swinton P, MacFarlane N. Relationships Between Training Load Variables in Professional Youth Football Players. *International journal of sports medicine*. 2020.
326. Maughan PC, MacFarlane NG, Swinton PA. Relationship Between Subjective and External Training Load Variables in Youth Soccer Players. *International journal of sports physiology and performance*. 2021:1-7.
327. Montini M, Rocchi JE. Monitoring Training Load in Soccer: The ROMEI Model. *Journal of strength and conditioning research*. 2020.

328. Silva P, Santos ED, Grishin M, Rocha JM. Validity of Heart Rate-Based Indices to Measure Training Load and Intensity in Elite Football Players. *Journal of strength and conditioning research*. 2018;32(8):2340-7.
329. Rago V, Brito J, Figueiredo P, Costa J, Barreira D, Krstrup P, et al. Methods to collect and interpret external training load using microtechnology incorporating GPS in professional football: a systematic review. *Res Sports Med*. 2020;28(3):437-58.
330. Oliveira R, Brito JP, Loureiro N, Padinha V, Ferreira B, Mendes B. Does the distribution of the weekly training load account for the match results of elite professional soccer players? *Physiology & behavior*. 2020;225:113118.
331. Abbott W, Brownlee TE, Harper LD, Naughton RJ, Richardson A, Clifford T. A season long investigation into the effects of injury, match selection and training load on mental wellbeing in professional under 23 soccer players: A team case study. *European journal of sport science*. 2019;19(9):1250-6.
332. Gallo T, Cormack S, Gabbett T, Williams M, Lorenzen C. Characteristics impacting on session rating of perceived exertion training load in Australian footballers. *Journal of sports sciences*. 2015;33(5):467-75.
333. Lovell TW, Sirotic AC, Impellizzeri FM, Coutts AJ. Factors affecting perception of effort (session rating of perceived exertion) during rugby league training. *International journal of sports physiology and performance*. 2013;8(1):62-9.
334. Delaney JA, Duthie GM, Thornton HR, Pyne DB. Quantifying the relationship between internal and external work in team sports: development of a novel training efficiency index. *Science and Medicine in Football*. 2018;2(2):149-56.
335. González-Fimbres RA, Ramírez-Siqueiros MG, Reynoso-Sánchez LF, Quezada-Chacón JT, Miranda-Mendoza J, Hernández-Cruz G. A new approach to quantify internal and external training load for intermittent sports. *Biotechnia*. 2019;21(3):26-34.
336. Lazarus BH, Stewart AM, White KM, Rowell AE, Esmaeili A, Hopkins WG, et al. Proposal of a global training load measure predicting match performance in an elite team sport. *Frontiers in physiology*. 2017;8:930.
337. Malone S, Doran D, Akubat I, Collins K. The Integration of Internal and External Training Load Metrics in Hurling. *Journal of human kinetics*. 2016;53:211-21.
338. Taylor RJ, Sanders D, Myers T, Akubat I. Reliability and Validity of Integrated External and Internal Load Ratios as Measures of Fitness in Academy Rugby Union Players. *Journal of strength and conditioning research*. 2020;34(6):1723-30.
339. Arazi H, Asadi A, Khalkhali F, Boullosa D, Hackney AC, Granacher U, et al. Association Between the Acute to Chronic Workload Ratio and Injury Occurrence in Young Male Team Soccer Players: A Preliminary Study. *Frontiers in physiology*. 2020;11:608.
340. Bowen L, Gross AS, Gimpel M, Bruce-Low S, Li FX. Spikes in acute:chronic workload ratio (ACWR) associated with a 5-7 times greater injury rate in English Premier League football players: a comprehensive 3-year study. *British journal of sports medicine*. 2020;54(12):731-8.
341. Bowen L, Gross AS, Gimpel M, Li F-X. Accumulated workloads and the acute: chronic workload ratio relate to injury risk in elite youth football players. *British journal of sports medicine*. 2017;51(5):452-9.
342. Delecroix B, McCall A, Dawson B, Berthoin S, Dupont G. Workload and non-contact injury incidence in elite football players competing in European leagues. *European journal of sport science*. 2018;18(9):1280-7.
343. Fuller CW. Modeling the impact of players' workload on the injury-burden of English Premier League football clubs. *Scandinavian journal of medicine & science in sports*. 2018;28(6):1715-21.
344. Howle K, Waterson A, Duffield R. Injury Incidence and Workloads during congested Schedules in Football. *International journal of sports medicine*. 2020;41(2):75-81.
345. Malone S, Owen A, Newton M, Mendes B, Collins KD, Gabbett TJ. The acute:chronic workload ratio in relation to injury risk in professional soccer. *J Sci Med Sport*. 2017;20(6):561-5.
346. McCall A, Dupont G, Ekstrand J. Internal workload and non-contact injury: a one-season study of five teams from the UEFA Elite Club Injury Study. *British journal of sports medicine*. 2018;52(23):1517-22.

347. McCall A, Jones M, Gelis L, Duncan C, Ehrmann F, Dupont G, et al. Monitoring loads and non-contact injury during the transition from club to National team prior to an international football tournament: A case study of the 2014 FIFA World Cup and 2015 Asia Cup. *J Sci Med Sport*. 2018;21(8):800-4.
348. Raya-González J, Nakamura FY, Castillo D, Yanci J, Fanchini M. Determining the Relationship Between Internal Load Markers and Noncontact Injuries in Young Elite Soccer Players. *International journal of sports physiology and performance*. 2019;14(4):421-5.
349. Sedeaud A, De Larochelambert Q, Moussa I, Brasse D, Berrou JM, Duncombe S, et al. Does an Optimal Relationship Between Injury Risk and Workload Represented by the "Sweet Spot" Really Exist? An Example From Elite French Soccer Players and Pentathletes. *Frontiers in physiology*. 2020;11:1034.
350. Suarez-Arrones L, De Alba B, Röhl M, Torreno I, Strütt S, Freyler K, et al. Player Monitoring in Professional Soccer: Spikes in Acute:Chronic Workload Are Dissociated From Injury Occurrence. *Frontiers in sports and active living*. 2020;2:75.
351. Griffin A, Kenny IC, Comyns TM, Lyons M. The Association Between the Acute:Chronic Workload Ratio and Injury and its Application in Team Sports: A Systematic Review. *Sports medicine (Auckland, NZ)*. 2020;50(3):561-80.
352. Nobari H, Aquino R, Clemente FM, Khalafi M, Adsuar JC, Pérez-Gómez J. Description of acute and chronic load, training monotony and strain over a season and its relationships with well-being status: A study in elite under-16 soccer players. *Physiology & behavior*. 2020;225:113117.
353. Impellizzeri FM, Menaspà P, Coutts AJ, Kalkhoven J, Menaspà MJ. Training Load and Its Role in Injury Prevention, Part I: Back to the Future. *J Athl Train*. 2020;55(9):885-92.
354. Oliver JL, Ayala F, De Ste Croix MBA, Lloyd RS, Myer GD, Read PJ. Using machine learning to improve our understanding of injury risk and prediction in elite male youth football players. *J Sci Med Sport*. 2020;23(11):1044-8.
355. Foster C, Rodriguez-Marroyo JA, de Koning JJ. Monitoring Training Loads: The Past, the Present, and the Future. *International journal of sports physiology and performance*. 2017;12(Suppl 2):S22-s8.
356. Bacon CS, Mauger AR. Prediction of overuse injuries in professional u18-u21 footballers using metrics of training distance and intensity. *The Journal of Strength & Conditioning Research*. 2017;31(11):3067-76.
357. Venturelli M, Schena F, Zanolli L, Bishop D. Injury risk factors in young soccer players detected by a multivariate survival model. *J Sci Med Sport*. 2011;14(4):293-8.
358. Rommers N, Rössler R, Verhagen E, Vandecasteele F, Verstockt S, Vaeyens R, et al. A Machine Learning Approach to Assess Injury Risk in Elite Youth Football Players. *Medicine and science in sports and exercise*. 2020;52(8):1745-51.
359. Bradley PS, Di Mascio M, Peart D, Olsen P, Sheldon BJTjos, research c. High-intensity activity profiles of elite soccer players at different performance levels. 2010;24(9):2343-51.
360. Bloomfield J, Polman R, O'Donoghue P. Physical demands of different positions in FA Premier League soccer. *Journal of sports science & medicine*. 2007;6(1):63.
361. Krstrup P, Mohr M, Ellingsgaard H, Bangsbo J. Physical demands during an elite female soccer game: importance of training status. *Medicine & Science in Sports & Exercise*. 2005;37(7):1242-8.
362. Stølen T, Chamari K, Castagna C, Wisløff U. Physiology of soccer: an update. *Sports medicine*. 2005;35:501-36.
363. Di Salvo V, Baron R, Tschan H, Montero FC, Bachl N, Pigozzi FJljasm. Performance characteristics according to playing position in elite soccer. 2007;28(03):222-7.
364. Abbott W, Brickley G, Smeeton NJ. Physical demands of playing position within English Premier League academy soccer. 2018.
365. Aslan A, Acikada C, Güvenç A, Gören H, Hazir T, Özkara AJJoss, et al. Metabolic demands of match performance in young soccer players. 2012;11(1):170.
366. Ademović AJHS. Differences in the quantity and intensity of playing in elite soccer players of different position in the game. 2016;18(1):26-31.
367. Orendurff MS, Walker JD, Jovanovic M, Tulchin KL, Levy M, Hoffmann DKJTJoS, et al. Intensity and duration of intermittent exercise and recovery during a soccer match. 2010;24(10):2683-92.

368. Ade J, Fitzpatrick J, Bradley PSJoss. High-intensity efforts in elite soccer matches and associated movement patterns, technical skills and tactical actions. Information for position-specific training drills. 2016;34(24):2205-14.
369. Bradley PS, Carling C, Archer D, Roberts J, Dodds A, Di Mascio M, et al. The effect of playing formation on high-intensity running and technical profiles in English FA Premier League soccer matches. 2011;29(8):821-30.
370. Gaudino P, Alberti G, Iaia FMJHms. Estimated metabolic and mechanical demands during different small-sided games in elite soccer players. 2014;36:123-33.
371. Clemente FM, Martins FML, Mendes RSJS, Journal C. Developing aerobic and anaerobic fitness using small-sided soccer games: Methodological proposals. 2014;36(3):76-87.
372. Clemente FM, Praça GM, Bredt S, van der Linden CMI, Serra-Olivares J. External Load Variations Between Medium- and Large-Sided Soccer Games: Ball Possession Games Vs Regular Games with Small Goals. Journal of human kinetics. 2019;70:191-8.
373. Castellano J, Puente A, Echeazarra I, Casamichana DJTJoS, Research C. Influence of the number of players and the relative pitch area per player on heart rate and physical demands in youth soccer. 2015;29(6):1683-91.
374. Ade JD, Harley JA, Bradley PS. Physiological response, time-motion characteristics, and reproducibility of various speed-endurance drills in elite youth soccer players: small-sided games versus generic running. International journal of sports physiology and performance. 2014;9(3):471-9.
375. Hill-Haas SV, Dawson BT, Coutts AJ, Rowsell GJJoss. Physiological responses and time–motion characteristics of various small-sided soccer games in youth players. 2009;27(1):1-8.
376. Rossi A, Pappalardo L, Cintia P. A Narrative Review for a Machine Learning Application in Sports: An Example Based on Injury Forecasting in Soccer. Sports (Basel, Switzerland). 2021;10(1).
377. Di Salvo V, Baron R, Tschan H, Montero FC, Bachl N, Pigozzi F. Performance characteristics according to playing position in elite soccer. International journal of sports medicine. 2006:222-7.
378. Pillitteri G, Giustino V, Petrucci M, Rossi A, Leale I, Bellafigliore M, et al. Match load physical demands in U-19 professional soccer players assessed by a wearable inertial sensor. Journal of Functional Morphology and Kinesiology. 2023;8(1):22.
379. Varley MC, Fairweather IH, Aughey1, Robert J. Validity and reliability of GPS for measuring instantaneous velocity during acceleration, deceleration, and constant motion. Journal of sports sciences. 2012;30(2):121-7.
380. Carlson JA, Jankowska MM, Meseck K, Godbole S, Natarajan L, Raab F, et al. Validity of PALMS GPS scoring of active and passive travel compared to SenseCam. 2015;47(3):662.
381. Duncan S, Stewart TI, Oliver M, Mavoa S, MacRae D, Badland HM, et al. Portable global positioning system receivers: static validity and environmental conditions. 2013;44(2):e19-e29.
382. Di Prampero P, Fusi SJSranealEB. Sepulcri L Morin JB Belli A Antonutto G. 2005;208:2809-16.
383. Minetti AE, Moia C, Roi GS, Susta D, Ferretti GJJJoap. Energy cost of walking and running at extreme uphill and downhill slopes. 2002.
384. Casamichana D, Castellano J, Castagna CJTJoS, Research C. Comparing the physical demands of friendly matches and small-sided games in semiprofessional soccer players. 2012;26(3):837-43.
385. Gabbett TJ, Nassis GP, Oetter E, Pretorius J, Johnston N, Medina D, et al. The athlete monitoring cycle: a practical guide to interpreting and applying training monitoring data. BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine; 2017. p. 1451-2.
386. Halson SLJSm. Monitoring training load to understand fatigue in athletes. 2014;44(Suppl 2):139-47.
387. Impellizzeri FM, Marcora SM, Coutts AJJJISPP. Internal and external training load: 15 years on. 2019;14(2):270-3.
388. Stølen T, Chamari K, Castagna C, Wisløff UJSm. Physiology of soccer: an update. 2005;35:501-36.
389. Pillitteri G, Giustino V, Petrucci M, Rossi A, Bellafigliore M, Thomas E, et al. External load profile during different sport-specific activities in semi-professional soccer players. 2023;15(1):22.
390. Varley MC, Jaspers A, Helsen WF, Malone JJJJjosp, performance. Methodological considerations when quantifying high-intensity efforts in team sport using global positioning system technology. 2017;12(8):1059-68.

391. Pillitteri G, Giustino V, Petrucci M, Rossi A, Leale I, Bellafore M, et al. Match Load Physical Demands in U-19 Professional Soccer Players Assessed by a Wearable Inertial Sensor. *Journal of functional morphology and kinesiology*. 2023;8(1).
392. Pillitteri G, Clemente FM, Petrucci M, Rossi A, Bellafore M, Bianco A, et al. Toward a New Conceptual Approach to “Intensity” in Soccer Player's Monitoring: A Narrative Review. 2023;37(9):1896-911.
393. Rojas-Valverde D, Gómez-Carmona CD, Gutiérrez-Vargas R, Pino-Ortega JJBos, medicine e. From big data mining to technical sport reports: The case of inertial measurement units. 2019;5(1):e000565.
394. Oliva-Lozano JM, Barbier X, Fortes V, Muyor JMJRiSM. Key load indicators and load variability in professional soccer players: a full season study. 2023;31(3):201-13.
395. Parmar N, James N, Hearne G, Jones BJJoPAiS. Using principal component analysis to develop performance indicators in professional rugby league. 2018;18(6):938-49.
396. Derbidge MC, Moody J, Byrne P. Can the Use of an External: Internal Ratio During Standardised Small-Sided Games be a Detector of Fatigue in Professional Adolescent Soccer Players? 2022.
397. Bowen L, Gross AS, Gimpel M, Bruce-Low S, Li F-XJBjasm. Spikes in acute: chronic workload ratio (ACWR) associated with a 5–7 times greater injury rate in English Premier League football players: a comprehensive 3-year study. 2020;54(12):731-8.
398. Griffin A, Kenny IC, Comyns TM, Lyons MJSM. The association between the acute: chronic workload ratio and injury and its application in team sports: a systematic review. 2020;50:561-80.
399. Pillitteri G, Thomas E, Battaglia G, Navarra GA, Scardina A, Gammio V, et al. Validity and reliability of an inertial sensor device for specific running patterns in soccer. 2021;21(21):7255.
400. Checkoway H, Pearce N, Kriebel D. Research methods in occupational epidemiology: Monographs in Epidemiology and; 2004.
401. Kriebel D, Checkoway H, Pearce NJO, medicine e. Exposure and dose modelling in occupational epidemiology. 2007;64(7):492-8.
402. Impellizzeri FM, Shrier I, McLaren SJ, Coutts AJ, McCall A, Slattery K, et al. Understanding training load as exposure and dose. 2023;1-13.
403. Coyne JO, Coutts AJ, Newton RU, Haff GGJSM-O. The current state of subjective training load monitoring: follow-up and future directions. 2022;8(1):53.
404. Impellizzeri F, Wookcock S, McCall A, Ward P, Coutts AJ. The acute-chronic workload ratio-injury figure and its ‘sweet spot’ are flawed. 2019.
405. Kenttä G, Hassmén PJSm. Overtraining and recovery: a conceptual model. 1998;26:1-16.
406. Nédélec M, McCall A, Carling C, Legall F, Berthoin S, Dupont G. Recovery in soccer: part I - post-match fatigue and time course of recovery. *Sports medicine (Auckland, NZ)*. 2012;42(12):997-1015.
407. Selmi O, Ouergui I, Muscella A, My G, Marsigliante S, Nobari H, et al. Monitoring Psychometric States of Recovery to Improve Performance in Soccer Players: A Brief Review. *Int J Environ Res Public Health*. 2022;19(15).
408. Clemente FM, Owen A, Serra-Olivares J, Nikolaidis PT, Van Der Linden CM, Mendes BJJohk. Characterization of the weekly external load profile of professional soccer teams from Portugal and the Netherlands. 2019;66(1):155-64.
409. Fessi MS, Zarrouk N, Di Salvo V, Filetti C, Barker AR, Moalla W. Effects of tapering on physical match activities in professional soccer players. *Journal of sports sciences*. 2016;34(24):2189-94.
410. Di Salvo V, Baron R, Tschan H, Montero FC, Bachl N, Pigozzi FJljasm. Performance characteristics according to playing position in elite soccer. 2006:222-7.
411. Di Salvo V, Pigozzi F, Gonzalez-Haro C, Laughlin M, De Witt JJJasm. Match performance comparison in top English soccer leagues. 2013;34(06):526-32.
412. Nobari H, Praça GM, da Glória Teles Bredt S, González PP, Clemente FM, Carlos-Vivas J, et al. Weekly variations of accelerometer variables and workload of professional soccer players from different positions throughout a season. 2023;13(1):2625.
413. Lupo C, Capranica L, Cortis C, Guidotti F, Bianco A, Tessitore AJTJasm, et al. Session-RPE for quantifying load of different youth taekwondo training sessions. 2016;57(3):189-94.

414. Torres-Ronda L, Beanland E, Whitehead S, Sweeting A, Clubb J. Tracking systems in team sports: a narrative review of applications of the data and sport specific analysis. *Sports Medicine-Open*. 2022;8(1):15.
415. Nédélec M, McCall A, Carling C, Legall F, Berthoin S, Dupont G. Recovery in soccer: part I—post-match fatigue and time course of recovery. *Sports medicine*. 2012;42:997-1015.
416. Silva H, Nakamura FY, Castellano J, Marcelino R. Training load within a soccer microcycle week—A systematic review. *Strength & Conditioning Journal*. 2023;45(5):568-77.
417. Oliva-Lozano JM, Gómez-Carmona CD, Fortes V, Pino-Ortega J. Effect of training day, match, and length of the microcycle on workload periodization in professional soccer players: a full-season study. *Biology of Sport*. 2022;39(2):397-406.
418. Pillitteri G, Giustino V, Petrucci M, Rossi A, Bellafigliore M, Thomas E, et al. External load profile during different sport-specific activities in semi-professional soccer players. *BMC Sports Science, Medicine and Rehabilitation*. 2023;15(1):22.
419. Gómez-Díaz A, Nakamura FY, Menezes P, Barreira J, Figueiredo P, Coutinho D. Characterizing microcycles' workload when combining two days structure within single training sessions during congested fixtures in an elite male soccer team. *Biology of Sport*. 2024;41(4):87-100.
420. Muazu Musa R, PP Abdul Majeed A, Taha Z, Chang SW, Ab. Nasir AF, Abdullah MR. A machine learning approach of predicting high potential archers by means of physical fitness indicators. *PLoS One*. 2019;14(1):e0209638.
421. Rico-González M, Pino-Ortega J, Méndez A, Clemente F, Baca A. Machine learning application in soccer: a systematic review. *Biology of sport*. 2023;40(1):249-63.
422. Di Salvo V, Baron R, Tschan H, Montero FC, Bachl N, Pigozzi F. Performance characteristics according to playing position in elite soccer. *International journal of sports medicine*. 2007;28(03):222-7.
423. Gualtieri A, Rampinini E, Sassi R, Beato M. Workload monitoring in top-level soccer players during congested fixture periods. *International journal of sports medicine*. 2020;41(10):677-81.
424. Rampinini E, Coutts AJ, Castagna C, Sassi R, Impellizzeri F. Variation in top level soccer match performance. *International journal of sports medicine*. 2007;28(12):1018-24.
425. Mandorino M, Figueiredo A, Cima G, Tessitore A. A data mining approach to predict non-contact injuries in young soccer players. *International Journal of Computer Science in Sport*. 2021;20(2):147-63.
426. Beato M, Wren C, de Keijzer KL. The interunit reliability of global navigation satellite systems Apex (STATSports) metrics during a standardized intermittent running activity. *The Journal of Strength & Conditioning Research*. 2022;10.1519.
427. Dawson L, Beato M, Devereux G, McErlain-Naylor SA. A Review of the Validity and Reliability of Accelerometer-Based Metrics From Upper Back–Mounted GNSS Player Tracking Systems for Athlete Training Load Monitoring. *The Journal of Strength & Conditioning Research*. 2022;10.1519.
428. Beato M, Coratella G, Stiff A, Iacono AD. The validity and between-unit variability of GNSS units (STATSports Apex 10 and 18 Hz) for measuring distance and peak speed in team sports. *Frontiers in physiology*. 2018;9:1288.
429. Beato M, de Keijzer K. The inter-unit and inter-model reliability of GNSS STATSports Apex and Viper units in measuring peak speed over 5, 10, 15, 20 and 30 meters. *Biology of sport*. 2019;36(4):317-21.
430. Ab Rasid AM, Muazu Musa R, Abdul Majeed AP, Musawi Maliki ABH, Abdullah MR, Mohd Razmaan MA, et al. Physical fitness and motor ability parameters as predictors for skateboarding performance: A logistic regression modelling analysis. *PLoS one*. 2024;19(2):e0296467.
431. Ke G, Meng Q, Finley T, Wang T, Chen W, Ma W, et al. Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*. 2017;30.
432. Adelsberger R, Tröster G, editors. Experts lift differently: Classification of weight-lifting athletes. 2013 IEEE international conference on body sensor networks; 2013: IEEE.
433. Trost SG, Wong W-K, Pfeiffer KA, Zheng Y. Artificial neural networks to predict activity type and energy expenditure in youth. *Medicine and science in sports and exercise*. 2012;44(9):1801.
434. Trost SG, Zheng Y, Wong W-K. Machine learning for activity recognition: hip versus wrist data. *Physiological measurement*. 2014;35(11):2183.

435. Muazu Musa R, PP Abdul Majeed A, Taha Z, Chang SW, Ab. Nasir AF, Abdullah MR (2019) A machine learning approach of predicting high potential archers by means of physical fitness indicators. *PLoS ONE*. 2019;14(1):e0209638.
436. Chicco D, Jurman G. The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. *BMC genomics*. 2020;21:1-13.
437. Hall MA. Correlation-based feature selection for machine learning: The University of Waikato; 1999.
438. Witten IH, Frank E, Hall MA, Pal CJ, Data M, editors. Practical machine learning tools and techniques. Data mining; 2005: Elsevier Amsterdam, The Netherlands.
439. Su N, Si G, Liang W, Bu D, Jiang X. Mindfulness and acceptance-based training for elite adolescent athletes: a mixed-method exploratory study. *Frontiers in Psychology*. 2024;15:1401763.
440. Zhou M, Chen GH, Ferreira P, Smith MD. Consumer behavior in the online classroom: Using video analytics and machine learning to understand the consumption of video courseware. *Journal of Marketing Research*. 2021;58(6):1079-100.
441. Oliva-Lozano JM, Barbier X, Fortes V, Muyor JMJRiSM. Key load indicators and load variability in professional soccer players: a full season study. 2021:1-13.
442. Sarmiento H, Martinho DV, Gouveia ÉR, Afonso J, Chmura P, Field A, et al. The Influence of Playing Position on Physical, Physiological, and Technical Demands in Adult Male Soccer Matches: A Systematic Scoping Review with Evidence Gap Map. *Sports Medicine*. 2024;54(11):2841-64.
443. Haddad M, Chaouachi A, Wong del P, Castagna C, Hambli M, Hue O, et al. Influence of fatigue, stress, muscle soreness and sleep on perceived exertion during submaximal effort. *Physiol Behav*. 2013;119:185-9.
444. Kellmann M, Bertollo M, Bosquet L, Brink M, Coutts AJ, Duffield R, et al. Recovery and Performance in Sport: Consensus Statement. *Int J Sports Physiol Perform*. 2018;13(2):240-5.
445. Mohr M, Krusturup P, Bangsbo J. Match performance of high-standard soccer players with special reference to development of fatigue. *Journal of sports sciences*. 2003;21(7):519-28.
446. Osiecki R, Rubio TBG, Coelho RL, Novack LF, Conde JHS, Alves CG, et al. The Total Quality Recovery Scale (TQR) as a proxy for determining athletes' recovery state after a professional soccer match. *Journal of Exercise Physiology Online*. 2015;18:27+.
447. Fransson D, Nielsen TS, Olsson K, Christensson T, Bradley PS, Fatouros IG, et al. Skeletal muscle and performance adaptations to high-intensity training in elite male soccer players: speed endurance runs versus small-sided game training. 2018;118(1):111-21.
448. Coutts A, Kempton T, Crowcroft S. Coutts, A. J., Crowcroft, S., & Kempton, T. (2018). Developing athlete monitoring systems: Theoretical basis and practical applications. In M. Kellmann & J. Beckmann (Eds.), *Sport, Recovery and Performance: Interdisciplinary Insights* (pp. 19-32). Abingdon: Routledge. 2018. p. 19-32.
449. Jeffries AC, Marcora SM, Coutts AJ, Wallace L, McCall A, Impellizzeri FM. Development of a Revised Conceptual Framework of Physical Training for Use in Research and Practice. *Sports medicine (Auckland, NZ)*. 2022;52(4):709-24.
450. Nedelec M, McCall A, Carling C, Legall F, Berthoin S, Dupont G. The influence of soccer playing actions on the recovery kinetics after a soccer match. *J Strength Cond Res*. 2014;28(6):1517-23.
451. Clemente FM, Silva R, Castillo D, Los Arcos A, Mendes B, Afonso J. Weekly Load Variations of Distance-Based Variables in Professional Soccer Players: A Full-Season Study. *Int J Environ Res Public Health*. 2020;17(9).
452. Guerrero-Calderón B, Fradua L, Morcillo JA, Castillo-Rodríguez AJTJoS, Research C. Analysis of the Competitive Weekly Microcycle in Elite Soccer: Comparison of Workload Behavior in Absolute and Relative Terms. 2022.
453. Vanrenterghem J, Nedergaard NJ, Robinson MA, Drust B. Training Load Monitoring in Team Sports: A Novel Framework Separating Physiological and Biomechanical Load-Adaptation Pathways. *Sports medicine (Auckland, NZ)*. 2017;47(11):2135-42.
454. Clemente FM, Martins FML, Mendes RS. Periodization Based on Small-Sided Soccer Games: Theoretical Considerations. 2014;36(5):34-43.

455. Martín-García A, Gómez Díaz A, Bradley PS, Morera F, Casamichana D. Quantification of a Professional Football Team's External Load Using a Microcycle Structure. *J Strength Cond Res*. 2018;32(12):3511-8.
456. Selmi O, Marzouki H, Ouergui I, BenKhalifa W, Bouassida A. Influence of intense training cycle and psychometric status on technical and physiological aspects performed during the small-sided games in soccer players. *Research in sports medicine (Print)*. 2018;26(4):401-12.
457. Silva A, Santhiago V, Papoti M, Gobatto C. Psychological, biochemical and physiological responses of Brazilian soccer players during a training program. *Science & Sports*. 2008;23:66-72.
458. Owen AL, Djaoui L, Newton M, Malone S, Mendes BJS, football mi. A contemporary multi-modal mechanical approach to training monitoring in elite professional soccer. 2017;1(3):216-21.
459. Nédélec M, Halson S, Abaidia AE, Ahmaidi S, Dupont G. Stress, Sleep and Recovery in Elite Soccer: A Critical Review of the Literature. *Sports medicine (Auckland, NZ)*. 2015;45(10):1387-400.
460. Gleeson M. Biochemical and immunological markers of over-training. *Journal of sports science & medicine*. 2002;1(2):31-41.
461. Nobari H, Alves AR, Haghighi H, Clemente FM, Carlos-Vivas J, Pérez-Gómez J, et al. Association between Training Load and Well-Being Measures in Young Soccer Players during a Season. *Int J Environ Res Public Health*. 2021;18(9).
462. Moalla W, Fessi MS, Farhat F, Nouira S, Wong DP, Dupont G. Relationship between daily training load and psychometric status of professional soccer players. *Research in sports medicine (Print)*. 2016;24(4):387-94.
463. Buchheit M, Racinais S, Bilsborough JC, Bourdon PC, Voss SC, Hocking J, et al. Monitoring fitness, fatigue and running performance during a pre-season training camp in elite football players. *J Sci Med Sport*. 2013;16(6):550-5.
464. Bellenger CR, Fuller JT, Thomson RL, Davison K, Robertson EY, Buckley JD. Monitoring Athletic Training Status Through Autonomic Heart Rate Regulation: A Systematic Review and Meta-Analysis. *Sports medicine (Auckland, NZ)*. 2016;46(10):1461-86.
465. Buchheit M, Simpson MB, Al Haddad H, Bourdon PC, Mendez-Villanueva A. Monitoring changes in physical performance with heart rate measures in young soccer players. *Eur J Appl Physiol*. 2012;112(2):711-23.
466. Meeusen R, Duclos M, Foster C, Fry A, Gleeson M, Nieman D, et al. Prevention, diagnosis, and treatment of the overtraining syndrome: joint consensus statement of the European College of Sport Science and the American College of Sports Medicine. *Med Sci Sports Exerc*. 2013;45(1):186-205.
467. Fessi MS, Nouira S, Dellal A, Owen A, Elloumi M, Moalla W. Changes of the psychophysical state and feeling of wellness of professional soccer players during pre-season and in-season periods. *Research in sports medicine (Print)*. 2016;24(4):375-86.
468. Gabriel H, Urhausen A, Valet G, Heidelberg U, Kindermann WJM, sports si, et al. Overtraining and immune system: a prospective longitudinal study in endurance athletes. 1998;30(7):1151-7.
469. Fernandes R, Brito JP, Vieira LHP, Martins AD, Clemente FM, Nobari H, et al. In-Season Internal Load and Wellness Variations in Professional Women Soccer Players: Comparisons between Playing Positions and Status. 2021;18(23):12817.
470. Kellmann M. Preventing overtraining in athletes in high-intensity sports and stress/recovery monitoring. *Scand J Med Sci Sports*. 2010;20 Suppl 2:95-102.
471. Buchheit M. Monitoring training status with HR measures: do all roads lead to Rome? *Front Physiol*. 2014;5:73.
472. Sandford GN, Laursen PB, Buchheit M. Anaerobic Speed/Power Reserve and Sport Performance: Scientific Basis, Current Applications and Future Directions. *Sports medicine (Auckland, NZ)*. 2021;51(10):2017-28.
473. Bestwick-Stevenson T, Toone R, Neupert E, Edwards K, Kluzek S. Assessment of Fatigue and Recovery in Sport: Narrative Review. *Int J Sports Med*. 2022;43(14):1151-62.
474. Taylor K-L, Chapman D, Cronin J, Newton M, Gill N. Fatigue Monitoring in High Performance Sport: A Survey of Current Trends. *Journal of Australian Strength and Conditioning*. 2012;20:12-23.

475. Gallo TF, Cormack SJ, Gabbett TJ, Lorenzen CH. Self-Reported Wellness Profiles of Professional Australian Football Players During the Competition Phase of the Season. *J Strength Cond Res.* 2017;31(2):495-502.
476. Nässi A, Ferrauti A, Meyer T, Pfeiffer M, Kellmann M. Development of two short measures for recovery and stress in sport. *Eur J Sport Sci.* 2017;17(7):894-903.
477. Selmi O, Ouerghi N, Khalifa WB, Jebabli N, Feki M, Bouassida A. Influence of Stress, Fatigue, Sleep and Delayed Onset Muscle Soreness on Perceived Physical Enjoyment Exertion during Small Sided Games. *Iran J Public Health.* 2018;47(3):449-50.
478. Clemente FM, Silva R, Chen YS, Aquino R, Praça GM, Castellano J, et al. Accelerometry-Workload Indices Concerning Different Levels of Participation during Congested Fixture Periods in Professional Soccer: A Pilot Study Conducted over a Full Season. *Int J Environ Res Public Health.* 2021;18(3).
479. Hooper SL, Mackinnon LT, Howard A, Gordon RD, Bachmann AW. Markers for monitoring overtraining and recovery. *Med Sci Sports Exerc.* 1995;27(1):106-12.
480. Selmi O, Gonçalves B, Ouerghi I, Sampaio J, Bouassida A. Influence of well-being variables and recovery state in physical enjoyment of professional soccer players during small-sided games. *Research in Sports Medicine.* 2018;26(2):199-210.
481. Pappalardo L, Guerrini L, Rossi A, Cintia P. Explainable Injury Forecasting via Multivariate Time Series and Convolutional Neural Networks 2019.
482. Vallance E, Sutton-Charani N, Imoussaten A, Montmain J, Perrey S. Combining Internal- and External-Training-Loads to Predict Non-Contact Injuries in Soccer. 2020;10(15):5261.
483. Rossi A, Pappalardo L, Cintia P. A Narrative Review for a Machine Learning Application in Sports: An Example Based on Injury Forecasting in Soccer. 2022;10(1):5.
484. Rossi A, Perri E, Trecroci A, Savino M, Alberti G, Iaia F. GPS Data Reflect Players' Internal Load in Soccer 2017.
485. Ekstrand J, Waldén M, Häggglund M. Hamstring injuries have increased by 4% annually in men's professional football, since 2001: a 13-year longitudinal analysis of the UEFA Elite Club injury study. *British journal of sports medicine.* 2016;50(12):731-7.
486. Van Dyk N, Behan FP, Whiteley R. Including the Nordic hamstring exercise in injury prevention programmes halves the rate of hamstring injuries: a systematic review and meta-analysis of 8459 athletes. *British journal of sports medicine.* 2019;53(21):1362-70.
487. Stubbe JH, Van Beijsterveldt A-MM, Van Der Knaap S, Stege J, Verhagen EA, Van Mechelen W, et al. Injuries in professional male soccer players in the Netherlands: a prospective cohort study. *Journal of athletic training.* 2015;50(2):211-6.
488. Opar DA, Williams MD, Timmins RG, Hickey J, Duhig SJ, Shield AJ. Eccentric hamstring strength and hamstring injury risk in Australian footballers. *Medicine & Science in Sports & Exercise.* 2015;47(4):857-65.
489. Watanabe S. Tree-structured parzen estimator: Understanding its algorithm components and their roles for better empirical performance. *arXiv preprint arXiv:230411127.* 2023.
490. Bittencourt NF, Meeuwisse W, Mendonça L, Nettel-Aguirre A, Ocarino J, Fonseca S. 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.* 2016;50(21):1309-14.
491. Buchheit M, Settembre M, Hader K, McHugh D. From High-Speed Running to Hobbling on Crutches: A Machine Learning Perspective on the Relationships Between Training Doses and Match Injury Trends.
492. Gregson W, Di Salvo V, Varley MC, Modonutti M, Belli A, Chamari K, et al. Harmful association of sprinting with muscle injury occurrence in professional soccer match-play: a two-season, league wide exploratory investigation from the Qatar Stars League. *Journal of science and medicine in sport.* 2020;23(2):134-8.
493. Andrade R, Wik EH, Rebelo-Marques A, Blanch P, Whiteley R, Espregueira-Mendes J, et al. Is the acute: chronic workload ratio (ACWR) associated with risk of time-loss injury in professional team sports? A systematic review of methodology, variables and injury risk in practical situations. 2020;50(9):1613-35.
494. Kalkhoven JT. Athletic injury research: frameworks, models and the need for causal knowledge. *Sports Medicine.* 2024;54(5):1121-37.

495. Edouard P, Mendiguchia J, Guex K, Lathi J, Samozino P, Morin J-B. Sprinting: a potential vaccine for hamstring injury? *Sport performance science reports*. 2019;2019.
496. Bowen L, Gross AS, Gimpel M, Bruce-Low S, Li F-X. Spikes in acute: chronic workload ratio (ACWR) associated with a 5–7 times greater injury rate in English Premier League football players: a comprehensive 3-year study. *British journal of sports medicine*. 2020;54(12):731-8.
497. Windt J, Zumbo BD, Sporer B, MacDonald K, Gabbett TJ. Why do workload spikes cause injuries, and which athletes are at higher risk? Mediators and moderators in workload–injury investigations. *BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine*; 2017. p. 993-4.
498. Bullock GS, Mylott J, Hughes T, Nicholson KF, Riley RD, Collins GS. Just how confident can we be in predicting sports injuries? A systematic review of the methodological conduct and performance of existing musculoskeletal injury prediction models in sport. *Sports medicine*. 2022;52(10):2469-82.
499. Hulin BT, Gabbett TJ, Blanch P, Chapman P, Bailey D, Orchard JW. Spikes in acute workload are associated with increased injury risk in elite cricket fast bowlers. *British journal of sports medicine*. 2014;48(8):708-12.
500. Duhig S, Shield AJ, Opar D, Gabbett TJ, Ferguson C, Williams M. Effect of high-speed running on hamstring strain injury risk. *British journal of sports medicine*. 2016;50(24):1536-40.
501. Dalen-Loretsen T, Bjørneboe J, Clarsen B, Vagle M, Fagerland MW, Andersen TE. Does load management using the acute:chronic workload ratio prevent health problems? A cluster randomised trial of 482 elite youth footballers of both sexes. *Br J Sports Med*. 2021;55(2):108-14.
502. Evans JSB. Hypothetical thinking: Dual processes in reasoning and judgement: Psychology Press; 2007.
503. Buchheit M, Laursen PB. High-intensity interval training, solutions to the programming puzzle: Part I: cardiopulmonary emphasis. *Sports medicine*. 2013;43(5):313-38.
504. Ekblom B. Applied physiology of soccer. *Sports medicine*. 1986;3:50-60.
505. Croisier J-L, Ganteaume S, Binet J, Genty M, Ferret J-M. Strength imbalances and prevention of hamstring injury in professional soccer players: a prospective study. *The American journal of sports medicine*. 2008;36(8):1469-75.
506. Engebretsen AH, Myklebust G, Holme I, Engebretsen L, Bahr R. Intrinsic risk factors for hamstring injuries among male soccer players: a prospective cohort study. *The American journal of sports medicine*. 2010;38(6):1147-53.
507. Hägglund M, Waldén M, Ekstrand J. Previous injury as a risk factor for injury in elite football: a prospective study over two consecutive seasons. *British journal of sports medicine*. 2006;40(9):767-72.
508. Askling C, Karlsson J, Thorstensson A. Hamstring injury occurrence in elite soccer players after preseason strength training with eccentric overload. *Scandinavian journal of medicine & science in sports*. 2003;13(4):244-50.
509. Askling C, Saartok T, Thorstensson A. Type of acute hamstring strain affects flexibility, strength, and time to return to pre-injury level. *British journal of sports medicine*. 2006;40(1):40-4.
510. Askling CM, Malliaropoulos N, Karlsson J. High-speed running type or stretching-type of hamstring injuries makes a difference to treatment and prognosis. *BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine*; 2012. p. 86-7.
511. Petersen J, Thorborg K, Nielsen MB, Budtz-Jørgensen E, Hölmich P. Preventive effect of eccentric training on acute hamstring injuries in men's soccer: a cluster-randomized controlled trial. *The American journal of sports medicine*. 2011;39(11):2296-303.
512. Kenneally-Dabrowski CJ, Brown NA, Lai AK, Perriman D, Spratford W, Serpell BG. Late swing or early stance? A narrative review of hamstring injury mechanisms during high-speed running. *Scandinavian Journal of Medicine & Science in Sports*. 2019;29(8):1083-91.
513. Garrett Jr WE. Muscle strain injuries. *The American journal of sports medicine*. 1996;24(6_suppl):S2-S8.
514. Lieber RL, Friden J. Muscle damage is not a function of muscle force but active muscle strain. *Journal of Applied Physiology*. 1993;74(2):520-6.
515. Mann R, Sprague P. A kinetic analysis of the ground leg during sprint running. *Research Quarterly for exercise and sport*. 1980;51(2):334-48.

516. Heiderscheit BC, Hoerth DM, Chumanov ES, Swanson SC, Thelen BJ, Thelen DG. Identifying the time of occurrence of a hamstring strain injury during treadmill running: a case study. *Clinical biomechanics*. 2005;20(10):1072-8.
517. Schache AG, Kim H-J, Morgan DL, Pandy MG. Hamstring muscle forces prior to and immediately following an acute sprinting-related muscle strain injury. *Gait & posture*. 2010;32(1):136-40.
518. Askling CM, Tengvar M, Saartok T, Thorstensson A. Acute first-time hamstring strains during high-speed running: a longitudinal study including clinical and magnetic resonance imaging findings. *The American journal of sports medicine*. 2007;35(2):197-206.
519. Orchard JW. Hamstrings are most susceptible to injury during the early stance phase of sprinting. *BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine*; 2012. p. 88-9.
520. Sun Y, Wei S, Zhong Y, Fu W, Li L, Liu Y. How joint torques affect hamstring injury risk in sprinting swing–stance transition. *Medicine and science in sports and exercise*. 2015;47(2):373.
521. Thelen DG, Chumanov ES, Best TM, Swanson SC, Heiderscheit BC. Simulation of biceps femoris musculotendon mechanics during the swing phase of sprinting. *Medicine & Science in Sports & Exercise*. 2005;37(11):1931-8.
522. Askling CM, Tengvar M, Saartok T, Thorstensson A. Acute first-time hamstring strains during slow-speed stretching: clinical, magnetic resonance imaging, and recovery characteristics. *The American journal of sports medicine*. 2007;35(10):1716-24.
523. Jones RI, Ryan B, Todd AI. Muscle fatigue induced by a soccer match-play simulation in amateur Black South African players. *Journal of sports sciences*. 2015;33(12):1305-11.
524. Schwiete C, Roth C, Skutschik C, Möck S, Rettenmaier L, Happ K, et al. Effects of muscle fatigue on exercise-induced hamstring muscle damage: a three-armed randomized controlled trial. *European Journal of Applied Physiology*. 2023;1-17.
525. Schuermans J, Van Tiggelen D, Danneels L, Witvrouw E. Susceptibility to hamstring injuries in soccer: a prospective study using muscle functional magnetic resonance imaging. *The American journal of sports medicine*. 2016;44(5):1276-85.
526. Bramah C, Mendiguchia J, Dos' Santos T, Morin J-B. Exploring the role of sprint biomechanics in hamstring strain injuries: a current opinion on existing concepts and evidence. *Sports Medicine*. 2023;1-11.
527. Aiello F, Di Claudio C, Fanchini M, Impellizzeri FM, McCall A, Sharp C, et al. Do non-contact injuries occur during high-speed running in elite football? Preliminary results from a novel GPS and video-based method. *Journal of science and medicine in sport*. 2023;26(9):465-70.
528. Teixeira JE, Forte P, Ferraz R, Leal M, Ribeiro J, Silva AJ, et al. Monitoring accumulated training and match load in football: A systematic review. *International Journal of Environmental Research and Public Health*. 2021;18(8):3906.
529. Danielsson A, Horvath A, Senorski C, Alentorn-Geli E, Garrett WE, Cugat R, et al. The mechanism of hamstring injuries—a systematic review. *BMC musculoskeletal disorders*. 2020;21:1-21.
530. Liu Y, Sun Y, Zhu W, Yu J. The late swing and early stance of sprinting are most hazardous for hamstring injuries. *Journal of sport and health science*. 2017;6(2):133.
531. Van Hooren B, Bosch F. Is there really an eccentric action of the hamstrings during the swing phase of high-speed running? part I: A critical review of the literature. *Journal of sports sciences*. 2017;35(23):2313-21.
532. Van Hooren B, Bosch F. Is there really an eccentric action of the hamstrings during the swing phase of high-speed running? Part II: Implications for exercise. *Journal of sports sciences*. 2017;35(23):2322-33.
533. Biewener AA. Muscle function in vivo: a comparison of muscles used for elastic energy savings versus muscles used to generate mechanical power1. *American Zoologist*. 1998;38(4):703-17.
534. McBride JM. Muscle actuators, not springs, drive maximal effort human locomotor performance. *Journal of Sports Science & Medicine*. 2021;20(4):766.
535. Holt NC, Roberts TJ, Askew GN. The energetic benefits of tendon springs in running: is the reduction of muscle work important? *Journal of Experimental Biology*. 2014;217(24):4365-71.
536. Lindstedt SL, LaStayo P, Reich T. When active muscles lengthen: properties and consequences of eccentric contractions. *Physiology*. 2001;16(6):256-61.

537. Chumanov ES, Heiderscheit BC, Thelen DG. The effect of speed and influence of individual muscles on hamstring mechanics during the swing phase of sprinting. *Journal of biomechanics*. 2007;40(16):3555-62.
538. Van Hooren B, Bosch F. Influence of muscle slack on high-intensity sport performance: A review. *Strength and Conditioning Journal*. 2016;38(5):75-87.
539. Jönhagen S, Ericson MO, Nemeth G, Eriksson E. Amplitude and timing of electromyographic activity during sprinting. *Scandinavian journal of medicine & science in sports*. 1996;6(1):15-21.
540. Rice N. Understanding Muscle Function during in vivo Locomotion Using a Novel Muscle Avatar Approach: Northern Arizona University; 2020.
541. Brenner B. Muscle mechanics and biochemical kinetics. *Molecular mechanisms in muscular contraction*. 1990:77-149.
542. Prince C, Morin J-B, Mendiguchia J, Lahti J, Guex K, Edouard P, et al. Sprint specificity of isolated hamstring-strengthening exercises in terms of muscle activity and force production. *Frontiers in sports and active living*. 2021;2:609636.
543. Smith Jr SC. Multiple risk factors for cardiovascular disease and diabetes mellitus. *The American journal of medicine*. 2007;120(3):S3-S11.
544. Evans JSB. Bias in human reasoning: Causes and consequences: Lawrence Erlbaum Associates, Inc; 1989.
545. Tversky A, Kahneman D. Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*. 1974;185(4157):1124-31.
546. Pohl R. Cognitive illusions: A handbook on fallacies and biases in thinking, judgement and memory: Psychology Press; 2004.
547. Legrenzi P, Girotto V, Johnson-Laird PN. Focussing in reasoning and decision making. *Cognition*. 1993;49(1-2):37-66.
548. Weston M. Training load monitoring in elite English soccer: a comparison of practices and perceptions between coaches and practitioners. *Science and Medicine in Football*. 2018;2(3):216-24.
549. Stanovich KE. Who is rational?: Studies of individual differences in reasoning: Psychology Press; 1999.
550. Ehrlinger J, Readinger WO, Kim B. Decision-making and cognitive biases. *Encyclopedia of mental health*. 2016;12(3):83-7.
551. Edwards WB. Modeling overuse injuries in sport as a mechanical fatigue phenomenon. *Exercise and sport sciences reviews*. 2018;46(4):224-31.
552. Kalkhoven JT, Watsford ML, Impellizzeri FM. A conceptual model and detailed framework for stress-related, strain-related, and overuse athletic injury. *Journal of science and medicine in sport*. 2020;23(8):726-34.
553. Gallagher S, Heberger JR. Examining the interaction of force and repetition on musculoskeletal disorder risk: a systematic literature review. *Human factors*. 2013;55(1):108-24.
554. Fung Y-c. Biomechanics: mechanical properties of living tissues: Springer Science & Business Media; 2013.
555. Hart NH, Nimphius S, Rantalainen T, Ireland A, Siafarikas A, Newton R. Mechanical basis of bone strength: influence of bone material, bone structure and muscle action. *Journal of musculoskeletal & neuronal interactions*. 2017;17(3):114.
556. Philippe P, Mansi O. Nonlinearity in the epidemiology of complex health and disease processes. *Theoretical medicine and bioethics*. 1998;19:591-607.
557. Hulme A, Finch CF. From monocausality to systems thinking: a complementary and alternative conceptual approach for better understanding the development and prevention of sports injury. *Injury epidemiology*. 2015;2(1):1-12.
558. Halson SL, Jeukendrup AEJSm. Does overtraining exist? 2004;34(14):967-81.
559. Borresen J, Lambert MIJSm. The quantification of training load, the training response and the effect on performance. 2009;39(9):779-95.
560. Bothwell LE, Greene JA, Podolsky SH, Jones DS. Assessing the gold standard—lessons from the history of RCTs. *N engl j med*. 2016;374(22):2175-81.

561. Jeffries AC, Marcora SM, Coutts AJ, Wallace L, McCall A, Impellizzeri FM. Development of a revised conceptual framework of physical training for use in research and practice. *Sports Medicine*. 2021;1-16.
562. Pffirmann D, Herbst M, Ingelfinger P, Simon P, Tug SJJ. Analysis of injury incidences in male professional adult and elite youth soccer players: a systematic review. 2016;51(5):410-24.
563. Hulin BT, Gabbett TJ, Lawson DW, Caputi P, Sampson JAJ. The acute: chronic workload ratio predicts injury: high chronic workload may decrease injury risk in elite rugby league players. 2016;50(4):231-6.
564. Malone S, Roe M, Doran DA, Gabbett TJ, Collins KDJ. Protection against spikes in workload with aerobic fitness and playing experience: the role of the acute: chronic workload ratio on injury risk in elite gaelic football. 2017;12(3):393-401.
565. Malone S, Hughes B, Doran DA, Collins K, Gabbett TJ. Can the workload–injury relationship be moderated by improved strength, speed and repeated-sprint qualities? 2019;22(1):29-34.
566. Hulin BT, Gabbett TJ. Indeed association does not equal prediction: the never-ending search for the perfect acute: chronic workload ratio. *BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine*; 2019. p. 144-5.
567. Lathlean TJH, Newstead SV, Gastin PB. Elite Junior Australian Football Players With Impaired Wellness Are at Increased Injury Risk at High Loads. *Sports Health*. 2023;15(2):218-26.
568. Ullah S, Gabbett TJ, Finch CF. Statistical modelling for recurrent events: an application to sports injuries. 2014;48(17):1287-93.

Appendix

6) Articles under review

Guglielmo Pillitteri, Rabi Muazu Musab, Filipe Manuel Clemente, Tindaro Bongiovanni, Marco Petrucci, Antonino Bianco, Marco Beato and Giuseppe Battaglia - Machine Learning Analysis of Intensity Profiles and Key Indicators in Standard Microcycle of Professional Soccer Players – *Journal of Sports Science*

Guglielmo Pillitteri, Filipe Manuel Clemente, Marco Petrucci, Hugo Sarmento, Antonio Figueiredo, Tindaro Bongiovanni, Antonino Bianco, Giuseppe Battaglia, Tim J. Gabbett - A New Conceptual Framework Explaining Hamstring Injuries In Soccer – How Do The Data-Informed Approach Support Practitioners In Protecting Players? A Brief Review – *Biology of Sports*

Pillitteri, Filipe Manuel Clemente, Marco Beato, Alessio Rossi, Hugo Sarmento, Antonio Palma, Antonino Bianco, Giuseppe Battaglia An Updated Conceptual Framework on Physical Performance and Training in Soccer. A narrative review - *Guglielmo – Strength and Conditioning Journal*

Guglielmo Pillitteri, Filipe Manuel Clemente, Jason Moran, Rafael Oliveira, Rui Miguel Silva, Hugo Sarmento, Giuseppe Puleo, Tindaro Bongiovanni, Marco Petrucci, Giuseppe Battaglia, Antonino Bianco - Are There Optimal Strength Training Methods for Soccer Players Exist? A Narrative Review of Methodological and Practical Implications – *Sports Medicine*

7) Co-authored abstracts

1. I. Leale, A. M. Parroco, M. Gómez-López, **G. Pillitteri**, V. Giustino and G. Battaglia (2023). The Influence of audience absence on “Sports Performance Share” in the Summer Paralympic Games. Abstract presented at the XIV National Congress SISMES Naples, Italy.
2. M. Petrucci, **G. Pillitteria**, I. Leale, A. Rossi, A. Bianco, A. Palma, G. Battaglia (2024). Match Load Physical Demands in U-19 Professional Soccer Players Assessed by a Wearable Inertial Sensor Abstract presented at the XV National Congress SISMES, Chieti, Italy. (Poster)

8) Co-supervised master thesis

1. "la prevenzione degli infortuni nel gioco del calcio"
2. "la riatletizzazione post infortuni muscolari nel calcio: revisione della letteratura sugli hamstring"
3. "prevenzione degli infortuni muscolari nel calcio: gli hamstring"
4. "la valutazione neuromuscolare nei giovani calciatori: effetti delle restrizioni dovute al covid 19"
5. "la figura del portiere nel gioco del calcio: il ruolo dell'allenamento nello sviluppo dei prerequisiti e dei fondamentali"
6. "gli infortuni muscolari nel calcio. il ruolo della flessibilità"
7. "il ruolo della fatica mentale nella prestazione sportiva"
8. "il ritorno allo sport dopo la rottura del legamento crociato anteriore nel calcio"
9. "il ritorno allo sport dopo infortunio del lca: una revisione della letteratura"
10. "l'infortunio del legamento crociato anteriore nel calciatore: riatletizzazione sul campo e return to play"
11. "analisi del carico esterno nel gioco del calcio – comparazione tra gare ufficiali ed esercitazioni tecnico-tattiche"
12. "la lesione muscolare degli hamstring: recupero funzionale e prevenzione"
13. "l'allenamento della forza nel calcio: metodologie a confronto per lo sviluppo della forza specifica"
14. "il ruolo del carico cognitivo e l'influenza della fatica mentale sulla prestazione calcistica: una revisione narrativa della letteratura"
15. "high intensity interval training nel calcio: una revisione della letteratura"
16. "la forza esplosiva nel giovane calciatore: valutazione e metodologie di allenamento"
17. "validazione della prestazione di tracciamento dati di un dispositivo elettronico inerziale in giovani calciatori"
18. "validazione di un dispositivo inerziale per il monitoraggio della prestazione del calciatore: gps e sistemi inerziali a confronto"
19. "il monitoraggio della prestazione del calciatore tramite dispositivi inerziali: una panoramica della letteratura"
20. "prevenzione degli infortuni muscolari nel gioco del calcio"
21. "la pubalgia nello sportivo: una revisione della letteratura"
22. "il ruolo del lattato nel calcio e le sue implicazioni con il carico esterno nelle diverse fasce d'età"
23. "il monitoraggio della prestazione nei giovani calciatori professionisti in partite ufficiali con l'utilizzo di un dispositivo inerziale"
24. "l'allenamento della forza nel calcio attraverso l'utilizzo delle macchine isoinerziali: una revisione della letteratura"
25. hit nel basket

26. “analisi del carico interno ed esterno in risposta all' allenamento tecnico-tattico ad alta intensita' nei giovani calciatori”
27. “l'agilità nel gioco del calcio: analisi delle metodologie di allenamento”
28. “prevenzione e riatletizzazione della pubalgia nel calciatore: aspetti teorici e strategie operative”
29. “recupero e riatletizzazione funzionale del ginocchio a seguito di lesione al legamento crociato anteriore: dall'evidenza scientifica all'esperienza sul campo”
30. “la prevenzione primaria degli infortuni da sovraccarico nel calciatore: una revisione della letteratura”
31. “il monitoraggio dell'allenamento nel calcio: l'utilizzo del gps negli small sided games: una revisione della letteratura”
32. “validazione di una scala di percezione dello sforzo per le esercitazioni ad alta intensità nei giovani giocatori di calcio”
33. “la riatletizzazione post-infortuni muscolari da non contatto nel calcio: una revisione della letteratura”
34. “la resistenza nel calcio: dalla valutazione alla programmazione dell'allenamento”