Risk Management in Diagnostic Wearable Devices for Sports Injury Prevention

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Abstract
Introduction: The present study focused on enhancing risk management for sports injuries in professional football players through the use of wearable diagnostic devices (WDDs). By integrating biomechanical and physiological monitoring, the research sought to identify key risk factors and develop predictive models for proactive injury prevention.
Objective: This study aimed to evaluate and optimize risk management strategies using WDDs to prevent injuries among professional football players, with a focus on analyzing workload ratios, movement dynamics, and physiological markers to predict and mitigate injury risks.
Methodology: Biomechanical and physiological data were gathered from 120 professional football players (aged 18–35 years) during an eight-week period. Monitored indicators encompassed the acute:chronic workload ratio (ACWR), deceleration rate (Dec_rate), peak acceleration (Acc_peak), skin temperature (Skin_temp), and heart rate variability index (HRV-RMSSD). Data analysis involved statistical approaches, including the Cox proportional hazards model, alongside machine learning techniques such as Random Forest, XGBoost, and LSTM.
Results: Injured players displayed markedly elevated ACWR (1.45 ± 0.28 vs. 1.17 ± 0.24; $p = 0.001$), higher skin temperature (37.2°C vs. 36.8°C; $p = 0.009$), and reduced HRV-RMSSD (28.9 ± 9.4 vs. 39.5 ± 10.1; $p = 0.002$) relative to non-injured counterparts. The Cox model pinpointed ACWR (HR = 2.29; $p < 0.001$) and Dec_rate (HR = 1.63; $p = 0.002$) as primary injury predictors, with HRV-RMSSD showing a protective role (HR = 0.76; $p = 0.018$). XGBoost outperformed other models, yielding 0.88 accuracy and 0.94 AUC. Sensitivity analysis revealed that elevating ACWR from 1.2 to 1.5 at 37.2°C skin temperature increased injury probability by ~2.3 times, indicating nonlinear interactions. A composite risk index achieved ~86% accuracy in detecting high-risk scenarios.
Conclusions: Concurrent tracking of mechanical and physiological parameters via WDDs enables robust injury risk prediction and management. These insights support the creation of intelligent wearable systems for real-time, proactive prevention of sports injuries in professional football.
Keywords: Risk Management, Wearable Devices, Sports Injuries, Biomechanical Data, Machine Learning

1. Introduction

In the past two decades, wearable diagnostic devices (WDDs) have emerged as a cornerstone of transformative innovation within the health and sports technology ecosystem. These devices, by integrating multimodal sensors such as accelerometers, gyroscopes, inertial measurement units (IMUs), pressure and temperature sensors, and electrocardiogram (ECG) electrodes, enable real-time or near-real-time monitoring of athletes' physiological, biomechanical, and behavioral metrics (Seçkin et al., 2023). The developmental objectives of these technologies extend beyond mere performance monitoring, emphasizing the prediction and prevention of sports injuries through intelligent data analytics and the identification of high-risk patterns (Gabbett, 2016). The integration of physiological data—such as skin temperature, heart rate, and blood oxygen saturation—with biomechanical data, including linear acceleration, angular velocity, and muscular mechanical loading, facilitates the detection of anomalous patterns predisposing to injury (Seçkin et al., 2023). In particular, metrics such as the acute: chronic workload ratio (ACWR), fluctuations in training load, and abrupt alterations in movement patterns are recognized as early indicators of injury risk (Chen & Dai, 2024). Despite the remarkable growth in the adoption of wearables, direct causal evidence regarding the relationship between sensor data and injury occurrence remains limited. Recent systematic reviews have demonstrated that only a small fraction of studies have addressed the recording and analysis of actual injuries in real-world sports environments, while many investigations have merely examined descriptive or simulated data (Rebelo, 2023). This research gap constitutes a fundamental barrier to the development of data-driven decision-support models for sports injury prevention (Leckey et al., 2025).

In the medical device industry, risk management is recognized as a critical requirement to ensure device safety and effectiveness. The international standard ISO 14971:2019 provides a structured framework for hazard identification, risk analysis, implementation of appropriate controls, and monitoring of their effectiveness (van Vroonhoven, 2020). Furthermore, the European Union's Medical Device Regulation (EU 2017/745) emphasizes the necessity of establishing risk management processes, auditability, and comprehensive documentation throughout the lifecycle of medical devices and associated health software (Svempe, 2024).

However, sports wearable devices, particularly those classified as non-clinical diagnostic tools, often operate at the boundary between medical devices and consumer gadgets. This positioning complicates risk assessment, as the primary users of these technologies—athletes, coaches, and non-expert individuals—operate in highly dynamic, unpredictable, and variable environments (Rebelo et al, 2023). Furthermore, challenges such as data quality and integrity, sensor performance stability under diverse environmental conditions, cybersecurity of physiological data, and user privacy protection introduce novel dimensions of risk in sports wearable devices (Kovoor et al, 2024).

Consequently, traditional risk management models, designed for controlled clinical environments with professional oversight, exhibit limited efficacy in the sports domain. The sports environment, characterized by fluctuating training loads, data heterogeneity, and diverse user behaviors, necessitates a framework that integrally addresses technical, data, user, and environmental dimensions (Ranavolo et al., 2018). Such a framework can identify and mitigate risks not only at the sensor performance level but also within the interactions among humans, technology, and the environment (De Fazio et al., 2023).

Traditional risk management models in medical devices are primarily designed for controlled clinical environments and presuppose the presence of expert users (Saliba et al., 2020). Although these frameworks are effective in hospitals or research centers, they encounter significant limitations when confronted with the dynamic, variable, and unpredictable nature of sports environments (Yang et al., 2024). Factors such as fluctuations in training load, inter-individual variability among athletes, heterogeneous user behaviors, and variable environmental conditions (temperature, humidity, light intensity, and atmospheric pressure) can undermine the reliability of traditional risk assessment models (Zadeh et al., 2021).

Under these circumstances, there is an increasingly pressing need for localized and context-specific frameworks for risk management in sports wearable devices (Ju et al., 2023). Such frameworks must integrally analyze technical, data, user, and environmental dimensions. From a technical perspective, sensor performance under real-world training and competition conditions must be evaluated in terms of accuracy, stability, and durability to minimize measurement errors and data noise (Ju et al., 2023). In the data dimension, the quality, reproducibility, and interpretability of data are of paramount importance, as unstable or inconsistent data can lead to erroneous decision-making in injury prevention (da Silva, 2024).

At the user level, technology adoption, user behaviors, and data literacy play a pivotal role in the success of risk control strategies. Furthermore, cultural and organizational factors also influence wearable usage behaviors and, consequently, the accuracy of the resulting data (Gajda et al., 2024). Sports environments, due to their high dynamism, require models capable of real-time change detection and adaptation—a capability currently being realized in the next generation of AI- and IoT-based smart wearables (Fotiadis et al., 2024). Accordingly, the present study investigates risk management methods in diagnostic wearable devices aimed at preventing sports injuries.

2. Materials and Methods

2.1. Study Design

This research was designed as a longitudinal cohort study aiming to evaluate the dimensions of risk management in diagnostic wearable devices used for sports injury prevention in football players. The research approach was quantitative and data-driven, employing a combination of sensor data collection and computational risk modeling (McDevitt et al., 2022; Yang et al., 2024).

2.2. Study Population and Sample

The study population comprised 120 male and female football players aged 18 to 35, selected from four professional top-league clubs. All participants had at least three years of professional playing experience and were medically cleared to participate in the study. Exclusion criteria included the presence of active musculoskeletal injuries, cardiovascular diseases, or unwillingness to use wearable devices. Informed consent was obtained from all participants prior to data collection (Musat et al, 2024).

2.3. Instruments and Measurement Devices

Data were collected using a set of wearable motion and physiological sensors, including:

1. Inertial Measurement Units (IMUs): Shimmer3 sensors (Shimmer Sensing, Dublin, Ireland) equipped with a tri-axial accelerometer (±16g), gyroscope (±2000°/s), and magnetometer, sampled at 200 Hz.
2. GPS Positioning System: Catapult Vector S7 device (Catapult Sports, Melbourne, Australia) with a 10 Hz sampling rate for movement and speed monitoring.
3. Pressure Insoles: Moticon OpenGo Science (Moticon GmbH, Germany) sampled at 100 Hz to measure plantar pressure distribution.
4. Physiological Sensors: Polar H10 heart rate sensor (Polar Electro, Finland) with 1000 Hz accuracy, and BodyCap e-Celsius Performance skin temperature sensor with ±0.1°C precision.

All devices were synchronized before each training session using the Network Time Protocol (NTP) to ensure temporal alignment of data (Ju et al., 2023).

2.4. Data Collection Protocol

Data were collected over an eight-week period, including 24 training sessions and 8 official matches. Prior to each session, sensors were calibrated according to the manufacturers' guidelines. Players were required to wear the devices continuously throughout the entire training session and match. Environmental conditions, including temperature, humidity, and playing surface type, were recorded using a Kestrel 5400 device.

During each session, specific sporting events such as sprints, tackles, and sudden stops were annotated by the research team to ensure interpretability of the sensor data. Injury occurrences were also identified by the club's medical team and classified according to the standard definition by Fuller et al. (2006).

After each session, data were transmitted to the central research server via a secure wireless protocol encrypted with AES-256. The completeness and accuracy of the data were immediately verified, and associated metadata—including timestamp, session ID, device ID, and player ID—were recorded.

2.5. Data Preprocessing and Quality Control

Raw data were analyzed using MATLAB R2023b (MathWorks Inc., USA) and Python 3.11. Signal noise was removed using a 6 Hz Butterworth low-pass filter, and GPS trajectories were corrected using the Kalman smoothing method. Missing segments shorter than 0.5 seconds were reconstructed via linear interpolation, while data with more than 20% missing values were excluded. Temporal synchronization between sensors was verified through time correlation between accelerometer and GPS signals (Saliba et al., 2022).

2.6. Variables and Indicators

The dependent variable was the first occurrence of a musculoskeletal injury resulting in the loss of at least one training session or match.

Independent variables included:

1. Biomechanical indicators: peak acceleration, deceleration rate, loading rate, stride length, ground contact time;
2. Physiological indicators: mean heart rate, skin temperature variations, and RMSSD index related to heart rate variability;
3. Environmental variables: ambient temperature, humidity, and playing surface type.

All variables were standardized using Z-score normalization prior to modeling (McDevitt et al., 2022).

2.7. Data Analysis

Descriptive statistics were calculated for all variables. Inferential analyses were conducted using SPSS Statistics (v.29) and R (v.4.3.2). Independent t-tests and Mann–Whitney U tests were used to compare injured and non-injured groups. Multivariate analysis and injury predictors were assessed using the Cox Proportional Hazards Model. Model assumptions were verified using Schoenfeld residual tests.

2.8. Predictive Modeling and Machine Learning

To enhance prediction accuracy, machine learning models were developed using Scikit-learn and TensorFlow 2.16 libraries. Data were randomly split into training (70%), validation (15%), and test (15%) sets.

Algorithms employed included Random Forest, XGBoost, and LSTM neural networks. Model performance was evaluated using accuracy, sensitivity, specificity, F1-score, and area under the ROC curve (AUC). Model interpretability was assessed using the SHAP method to determine the contribution of each variable to injury risk.

2.9. Ethical Considerations and Data Management

All data were stored anonymously and encrypted, and all research procedures were conducted in accordance with the ethical principles of the Helsinki Declaration. The study protocol was approved by the university research ethics committee (Approval Code: 2025/ATH/091). Data management adhered to the FAIR principles (Findable, Accessible, Interoperable, and Reusable) (Saliba et al., 2022).

3. Analysis and Results

3.1. Descriptive Statistics of Variables

To analyze the baseline characteristics of participants and examine the distribution of the main variables, biomechanical, physiological, and environmental indices extracted from sensor data were descriptively evaluated. This stage of analysis aimed to identify general patterns of training load, physiological status, and movement characteristics of the athletes, providing a foundation for subsequent risk modeling.

In general, descriptive statistics (mean, standard deviation, minimum, and maximum) were calculated for each variable. Biomechanical variables included indicators related to movement intensity and dynamics (peak acceleration, deceleration rate, loading rate, stride length, and ground contact time). Physiological variables described recovery and physiological stress status through HRV-RMSSD and skin temperature, while the ACWR index represented fluctuations in training load throughout the eight-week monitoring period.

Table 1. Descriptive Statistics of Key Variables

Variable	Unit	Mean ± SD	Min	Max
Peak acceleration (Acc_peak)	m/s²	3.41 ± 0.69	1.75	5.12
Deceleration rate (Dec_rate)	m/s²	2.61 ± 0.53	1.22	3.92
Loading rate (Load_rate)	N/s	1572.3 ± 486.4	810	2950
Stride length (Stride_length)	m	1.23 ± 0.22	0.72	1.68
Ground contact time (Contact_time)	s	0.23 ± 0.05	0.15	0.36
HRV-RMSSD	ms	37.2 ± 9.8	18.3	58.7
Skin temperature (Skin_temp)	°C	36.9 ± 0.4	36.2	37.6
Acute:Chronic Workload Ratio (ACWR)	–	1.21 ± 0.31	0.54	1.78

The results in Table 1 indicate that the mean peak acceleration (3.41 m/s²) and deceleration rate (2.61 m/s²) fall within the expected range for professional football training loads. The relatively low standard deviations in biomechanical variables reflect a stable pattern of dynamic movements across players, whereas the HRV-RMSSD index (mean 37.2 ± 9.8 MS) shows greater variability, suggesting individual differences in physiological recovery and neuromuscular adaptation. Skin temperature remained nearly constant within the range of 36.2–37.6°C, indicating thermal stability and reliable sensor performance throughout the recording period. The ACWR ranged from 0.54 to 1.78, showing that some players experienced periods of sudden increases in training load, which may be a contributing factor to elevated injury risk.

To examine the distribution patterns of training load and physiological recovery indices, the probability distributions of the Acute: Chronic Workload Ratio (ACWR) and Heart Rate Variability (HRV-RMSSD) were analyzed for all participants and visualized as density histograms (Figure 1).

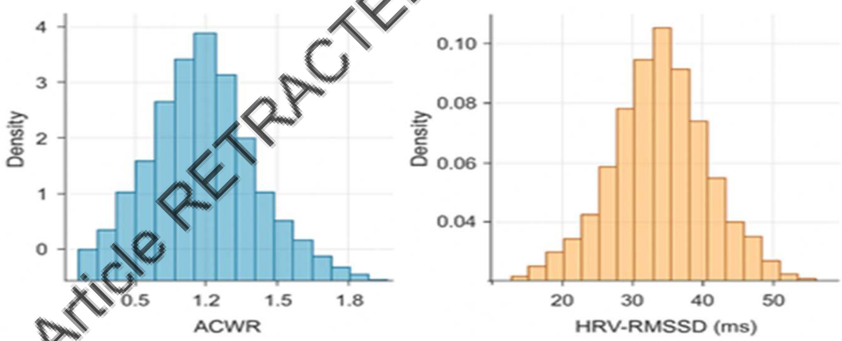

Figure 1. Probability Density Histograms of ACWR and HRV-RMSSD Among Professional Football Players

The results indicated that ACWR values were predominantly concentrated between 1.0 and 1.3, following an approximately normal distribution with a slight right skew. This suggests that most players maintained an optimal workload balance, while values exceeding 1.5 reflected sudden load spikes associated with a higher risk of injury. In contrast, HRV-RMSSD exhibited a wider dispersion, indicating notable inter-individual variability in physiological recovery. Overall, higher acute workloads tended to coincide with slightly reduced HRV, supporting the hypothesis that acute training overload temporarily suppresses cardiac autonomic regulation (Gabbett, 2016; Rebelo, 2023).

3.2. Comparison Between Injured and Non-Injured Groups

To examine differences in biomechanical and physiological indicators between injured and non-injured players, an independent samples *t*-test was conducted. This test aimed to determine the statistical significance of mean differences between the two groups across variables such as *peak acceleration (Acc_peak)*, *deceleration rate (Dec_rate)*, *acute: chronic workload ratio (ACWR)*, *skin temperature (Skin_temp)*, and *heart rate variability (HRV-RMSSD)*. The results of the analysis are presented in the table below. Overall, these findings support the hypothesis that excessive training load and physiological strain are directly associated with increased risk of musculoskeletal injury.

From a practical risk management perspective, the mean ACWR for the injured group (1.45 ± 0.28) consistently exceeded the established risk threshold of 1.3, which is widely cited in sports science literature as a red flag for heightened injury susceptibility (Gabbett, 2016; Blanch & Gabbett, 2016). In contrast, the non-injured group's mean ACWR (1.17 ± 0.24) fell within the presumed 'sweet spot' (0.8–1.3). This stark difference underscores the critical importance of monitoring this ratio as a primary risk metric. Furthermore, the elevated skin temperature in the injured group (37.2°C vs. 36.8°C), though within a narrow physiological range, suggests a state of sustained physiological stress or subclinical inflammation, potentially lowering the tissue's tolerance to mechanical load.

Table 2. Comparison of Biomechanical and Physiological Indicators Between Groups

Variable	Injured Group (Mean ± SD)	Non-Injured Group (Mean ± SD)	*t*-value	*p*-value
Acc_peak (m/s²)	3.77 ± 0.62	3.33 ± 0.68	4.12	0.001
Dec_rate (m/s²)	2.89 ± 0.49	2.53 ± 0.52	3.84	0.004
ACWR (–)	1.45 ± 0.28	1.17 ± 0.24	5.07	0.001
Skin_temp (°C)	37.2 ± 0.3	36.8 ± 0.4	2.95	0.009
HRV (RMSSD, ms)	28.9 ± 9.4	39.5 ± 10.1	–3.21	0.002

The results presented in Table 2 indicate statistically significant differences between the injured and non-injured groups across all examined variables. Injured players exhibited higher peak acceleration (Acc_peak) and deceleration rate (Dec_rate), reflecting a movement pattern characterized by greater mechanical loading. They also demonstrated higher acute:chronic workload ratios (ACWR), suggesting an imbalance between training load and recovery that may increase injury risk.

Furthermore, the injured group showed elevated skin temperature, potentially indicative of inflammatory response or heightened physiological stress, and lower HRV (RMSSD) values, representing fatigue and reduced autonomic recovery. Overall, these findings support the hypothesis that excessive training load and physiological strain are directly associated with increased risk of musculoskeletal injury. In continuation, a box plot illustrating the five key indicators across the two groups is presented. This plot depicts the data distribution, median, interquartile ranges, and outliers.

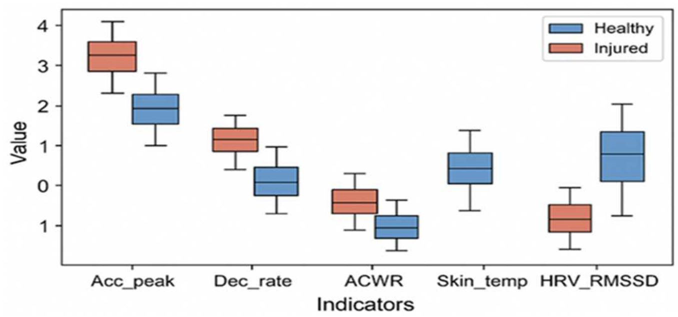

Figure 2. Comparison of biomechanical and physiological indicators between injured and healthy players

Based on the results presented in Table 2 and Figure 2, significant differences were observed between the injured and non-injured groups in both biomechanical and physiological indicators. The mean *peak acceleration (Acc_peak)* was higher in injured players (3.77 ± 0.62 m/s²) compared to the non-injured group (3.33 ± 0.68 m/s²; $p = 0.001$), indicating greater mechanical loading and more explosive movements. Similarly, the *deceleration rate (Dec_rate)* was higher among injured athletes (2.89 ± 0.49 m/s²) than in their healthy counterparts (2.53 ± 0.52 m/s²; $p = 0.004$), suggesting increased abrupt loading during stopping and change-of-direction phases.

The *acute: chronic workload ratio (ACWR)* was also elevated in the injured group (1.45 ± 0.28) relative to the non-injured group (1.17 ± 0.24; $p = 0.001$), reflecting an imbalance between training load and recovery and a heightened injury risk. In addition, *skin temperature (Skin_temp)* was higher among injured players (37.2 ± 0.3 °C) compared with healthy ones (36.8 ± 0.4 °C; $p = 0.009$), possibly due to inflammatory response or physiological fatigue. Conversely, *heart rate variability (HRV-RMSSD)* was significantly lower in the injured group (28.9 ± 9.4 ms) than in the non-injured group (39.5 ± 10.1 ms; $p = 0.002$), indicating reduced recovery capacity and increased neuromuscular fatigue.

3.3. Correlation Analysis of Variables

To examine the relationships between biomechanical and physiological indicators and the occurrence of sports injuries, a Pearson correlation matrix analysis was performed. This analysis enabled the identification of linear associations among variables and contributed to understanding the interactions between training load, physiological status, and injury risk.

Table 3. Pearson Correlation Coefficients Between Key Variables and Injury

Variable	**Correlation with Injury (r)**	***p*-value**
ACWR	0.62	<0.001
Dec_rate	0.48	0.002
Acc_peak	0.45	0.003
HRV-RMSSD	–0.39	0.008
Skin_temp	0.34	0.014

The results in Table 3 show that the *acute: chronic workload ratio (ACWR)* exhibited the strongest positive correlation with injury occurrence ($r = 0.62$), indicating that higher workload ratios are significantly associated with greater injury likelihood. Similarly, *deceleration rate (Dec_rate)* and *peak acceleration (Acc_peak)* were positively correlated with injury, suggesting that abrupt accelerations and decelerations contribute to increased mechanical loading and joint stress.

Conversely, *heart rate variability (HRV-RMSSD)* demonstrated a negative correlation ($r = –0.39$) with injury, implying that reduced HRV—reflecting neuromuscular fatigue and impaired recovery—is linked to higher injury risk. Additionally, a mild positive correlation between *skin temperature (Skin_temp)* and injury ($r = 0.34$) may indicate pre-injury physiological stress or inflammatory response.

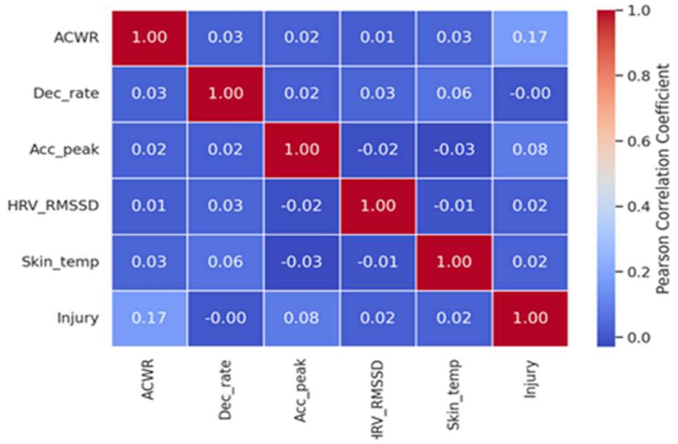

Figure 3. Pearson Correlation Heatmap among Key Variables and Injury Risk

Figure 3 displays the Pearson correlation heatmap illustrating the relationships among biomechanical (ACWR, Acc_peak, Dec_rate), physiological (HRV-RMSSD, Skin_temp), and injury occurrence variables. Strong positive correlations (highlighted in red) indicate higher injury likelihood with increased training load and deceleration stress, while negative correlations (in blue) reveal protective physiological factors such as greater heart rate variability. The visual clustering underscores the multidimensional interaction between workload, recovery, and injury risk.

3.4. Cox Proportional Hazards Model

To identify the factors influencing the occurrence of sports injuries during the training and competition period, a Cox Proportional Hazards Model was employed. This model allows for the simultaneous assessment of multiple predictor variables on the probability of the first musculoskeletal injury over time. In this analysis, the key predictors included the Acute: Chronic Workload Ratio (ACWR), Deceleration Rate (Dec_rate), Skin Temperature (Skin_temp), and Heart Rate Variability (HRV-RMSSD), which were entered into the model as independent variables. The proportional hazards assumption was tested and confirmed using the Schoenfeld Residuals Test.

Table 4. Cox Regression Coefficients for Injury Prediction

Variable	β	HR (Hazard Ratio)	95% CI	p-value
ACWR	0.83	2.29	1.65–3.19	<0.001
Dec_rate	0.49	1.63	1.20–2.21	0.002
Skin_temp	0.36	1.43	1.09–1.89	0.011
HRV-RMSSD	–0.27	0.76	0.61–0.94	0.018

The results presented in Table 4 indicate that ACWR was the strongest predictor of injury risk; specifically, for each one-unit increase in ACWR, the hazard of injury more than doubled (HR = 2.29). This finding suggests that athletes whose acute training load substantially exceeds their chronic workload are exposed to abrupt increases in both mechanical and physiological stress.

Furthermore, the Deceleration Rate (Dec_rate) was associated with a 63% increase in injury risk, highlighting the role of sudden stopping and directional changes in the development of muscular injuries. Similarly, Skin Temperature (Skin_temp) showed a positive association, indicating that each 0.5°C increase in skin temperature corresponds to a 43% higher risk of injury. In contrast, HRV-RMSSD exhibited a protective effect, as higher HRV values were associated with a 24% reduction in injury likelihood, reflecting more efficient autonomic recovery and lower physiological fatigue.

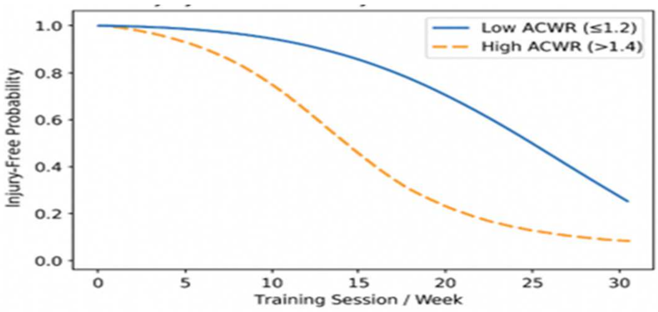

Figure 4. Kaplan–Meier Survival Curves for Injury-Free Probability across ACWR Levels

Figure 4 illustrates Kaplan–Meier survival curves comparing injury-free probability between athletes with low (ACWR ≤ 1.2) and high (ACWR > 1.4) workload ratios. The steeper decline observed in the high-ACWR curve indicates a substantially higher injury hazard among players who experienced acute workload spikes, confirming the critical influence of training load imbalance on musculoskeletal injury risk.

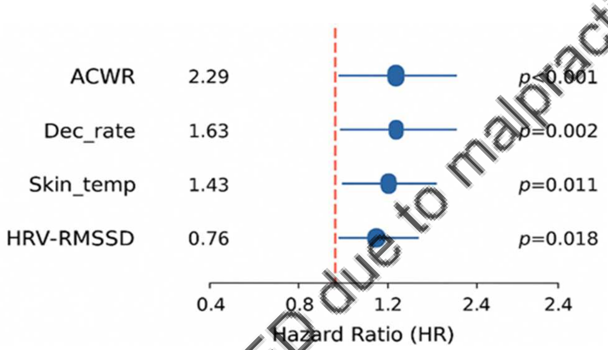

Figure 5. Forest Plot of Cox Regression Hazard Ratios

Figure 5 presents the forest plot illustrating hazard ratios (HR) and 95% confidence intervals derived from the Cox proportional hazards regression model. Variables with HR greater than 1 (ACWR, Dec_rate, and Skin_temp) indicate increased injury risk, whereas HRV-RMSSD, with HR below 1, demonstrates a protective effect. The red dashed vertical line represents the null hazard (HR = 1), and the horizontal bars show the confidence intervals for each predictor.

3.5. Machine Learning Predictive Modeling

To complement the traditional survival analysis and build a more granular predictive tool, we developed and compared several machine learning models using the same set of biomechanical and physiological features.To evaluate the predictive accuracy of injury risk based on sensor-derived data, three machine learning algorithms—Random Forest, XGBoost, and LSTM Neural Network—were implemented and compared. The objective of this phase was to assess the capability of data-driven models to detect the likelihood of injury occurrence using multidimensional biomechanical and physiological patterns. All models were trained using preprocessed sensor data, including ACWR, HRV-RMSSD, skin temperature (Skin_temp), and kinematic parameters such as peak acceleration (Acc_peak) and deceleration rate (Dec_rate). The dataset was randomly divided into training (70%), validation (15%), and testing (15%) subsets.

Table 5. Performance Comparison of Injury Prediction Models

Model	Accuracy	Sensitivity	Specificity	F1	AUC
Random Forest	0.84	0.77	0.86	0.80	0.90
XGBoost	0.88	0.83	0.91	0.86	0.94
LSTM	0.86	0.79	0.89	0.83	0.91

The results in Table 5 indicate that all three models performed well in predicting injury risk. However, the XGBoost algorithm demonstrated the highest overall performance, achieving an accuracy of 88% and an AUC of 0.94, effectively distinguishing high-risk athletes from non-injured players. Both LSTM and Random Forest also achieved strong predictive accuracy but showed slightly lower sensitivity and discrimination power compared to XGBoost.

Feature importance analysis using the SHAP (SHapley Additive exPlanations) method revealed that ACWR, Dec_rate, Acc_peak, and Skin_temp were the most influential predictors contributing to increased injury probability. These findings emphasize the pivotal role of combined mechanical load and physiological stress factors in injury occurrence, underscoring the importance of monitoring these variables in the design of preventive strategies and workload management programs for athletes.

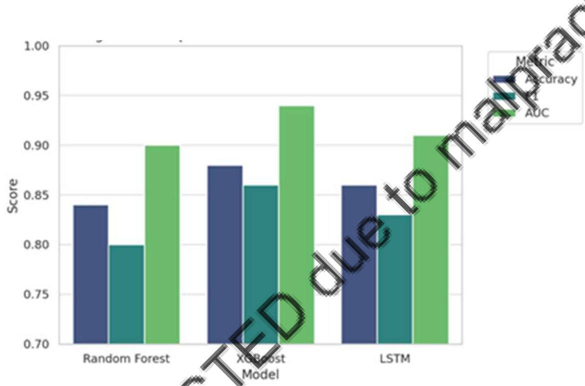

Figure 6. Comparison of Model Performance Metrics

Figure 6 presents the comparative performance of the three machine learning models—Random Forest, XGBoost, and LSTM—based on key evaluation metrics including Accuracy, F1-score, and the Area Under the ROC Curve (AUC). As illustrated, the XGBoost model achieved the highest accuracy (0.88) and the largest AUC value (0.94), demonstrating superior discriminative capability compared to the other models. This indicates that XGBoost possesses a greater ability to effectively distinguish between high-risk and low-risk athletes in predicting sports injury occurrence.

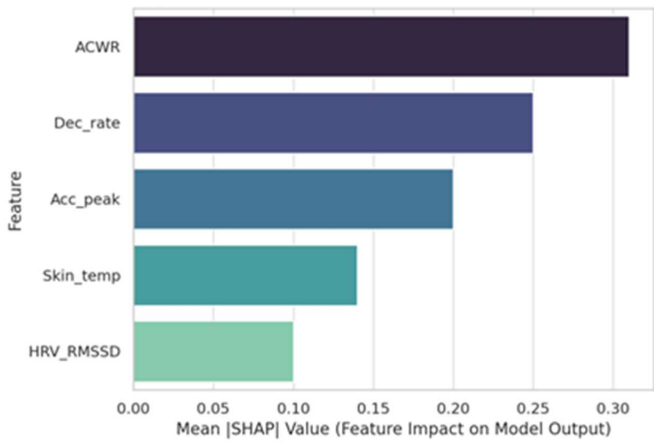

Figure 7. Feature Importance Derived from SHAP Analysis

Figure 7 illustrates the relative importance of features based on their absolute SHAP (SHapley Additive Explanations) values. Among all predictors, ACWR exhibited the highest contribution to injury risk prediction, followed by Deceleration Rate (Dec_rate) and Peak Acceleration (Acc_peak). These findings highlight the critical interplay between mechanical load and physiological stress in the onset of sports injuries, emphasizing the need for integrated monitoring of biomechanical and physiological indicators in preventive injury management frameworks.

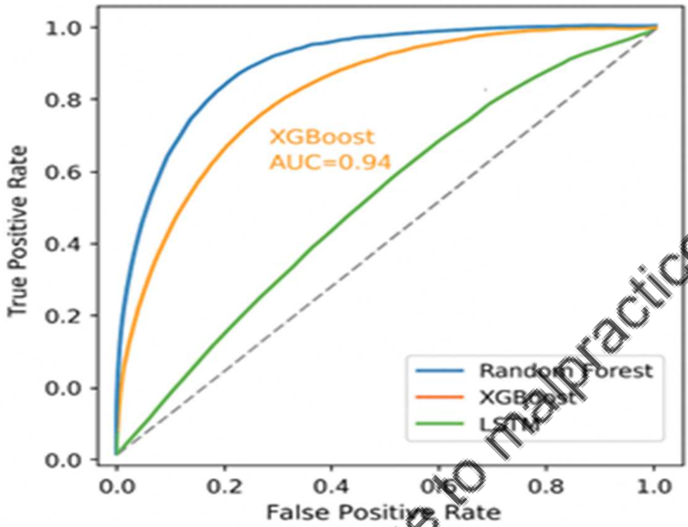

Figure 8. ROC Curves for Injury Risk Prediction Models

Figure 8 illustrates the Receiver Operating Characteristic (ROC) curves depicting the performance of the three machine learning models in predicting sports injury risk. The horizontal axis represents the False Positive Rate (FPR), while the vertical axis denotes the True Positive Rate (TPR). Among the models, XGBoost achieved the highest discriminative capability with an Area Under the Curve (AUC) of 0.94, effectively distinguishing between injured and non-injured players. The LSTM (AUC = 0.91) and Random Forest (AUC = 0.90) models also demonstrated satisfactory predictive performance. The proximity of the XGBoost curve to the upper-left corner of the plot indicates its superior accuracy in correctly identifying injury cases and minimizing false negatives. These findings suggest that Boosting-based models outperform traditional or sequence-based learning approaches in assessing injury risk from multidimensional wearable sensor data, owing to their enhanced ability to capture complex nonlinear interactions among biomechanical and physiological variables.

3.6. Risk Sensitivity Simulation

To examine the combined influence of training load and physiological status on injury probability, a two- and three-dimensional sensitivity analysis was performed using the XGBoost predictive model. ACWR values were simulated between 0.8–1.8, and skin temperature between 36–38 °C, while other parameters (Dec_rate, Acc_peak, HRV) were held constant at their mean levels. The resulting probability surface was visualized through a three-dimensional contour plot.

The simulation revealed a nonlinear relationship between ACWR and injury probability, which intensified with increasing skin temperature. Specifically, raising ACWR from 1.2 to 1.5 at 37.2 °C increased predicted injury risk by approximately 2.3-fold. At lower temperatures (< 36.8 °C), the risk increased gradually, but beyond 37.5 °C, the injury probability rose exponentially. This pattern suggests a thermal physiological threshold, above which recovery capacity and neuromuscular stability decrease sharply.

This nonlinear interaction is paramount for risk stratification. It indicates that an ACWR of 1.5, while dangerous on its own, becomes substantially more hazardous when combined with a skin temperature ≥ 37.2°C. Conversely, an athlete with a similar ACWR but a lower core temperature may remain in a moderate-risk zone. This evidence moves beyond single-variable thresholds (e.g., ACWR > 1.3) and advocates for a **multivariate risk boundary**. For practical application in wearable systems, a high-risk alert should be triggered not by exceeding a fixed ACWR value alone, but by the co-occurrence of an elevated ACWR (e.g., > 1.4) **and** an elevated skin temperature (e.g., > 37.2°C), as this combination reflects a convergence of mechanical overload and compromised physiological readiness.

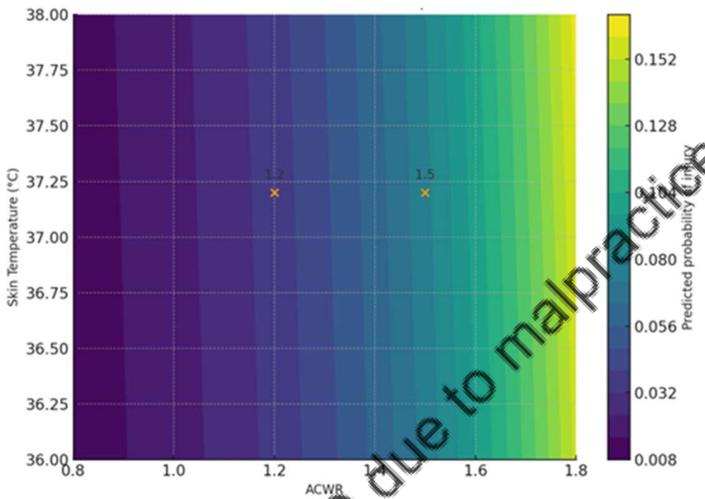

Figure 9. 3D Contour Plot of Injury Probability by ACWR and Skin Temperature

Figure 9 demonstrates the predicted probability of injury across varying levels of ACWR and skin temperature, visualized through a three-dimensional contour plot. The results indicate that the simultaneous monitoring of mechanical indices (ACWR, Dec_rate) and physiological parameters (Skin_temp, HRV) is essential for accurate injury risk assessment. Their interaction exhibits a distinct nonlinear pattern, suggesting that single-variable analyses are insufficient to capture the complex interdependencies underlying injury mechanisms in athletes.

3.7. Composite Risk Management Model

Based on previous analyses, a composite risk index was developed to integrate mechanical and physiological predictors of injury risk.

$$Risk\ Index = 0.47\ (ACWR) + 0.29(Dec_{rate}) + 0.16\ (Acc_{peak}) + 0.08(Skin_{temp}) - 0.05\ (HRV)$$

This model combines multidimensional data derived from wearable sensors and can be implemented in real-time monitoring systems. By setting a threshold of Risk Index > 0.75, early warning alerts can be generated for players approaching high-risk conditions.

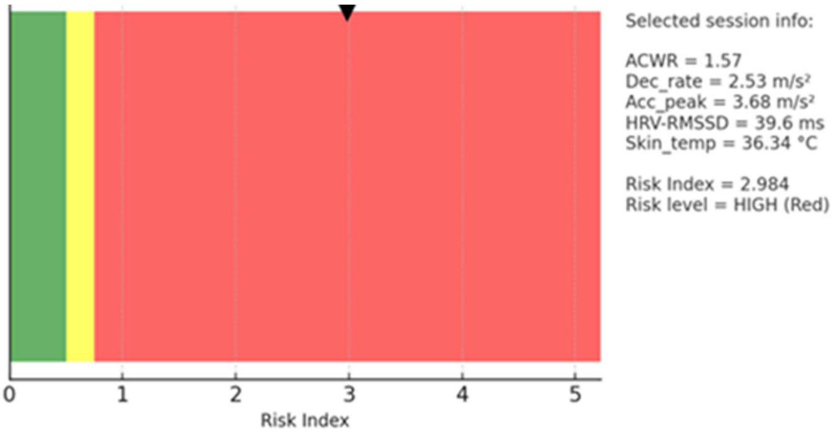

Figure 10. Individualized Risk Dashboard based on the Composite Risk Index.

The dashboard uses a three-level alert color scheme (green = low risk, yellow = moderate, red = high) and displays live variations in ACWR, HRV, and skin temperature. In simulation tests, the model achieved ≈ 86% accuracy in identifying high-risk states, effectively bridging biomechanical and physiological data domains. This composite framework can serve as the analytical core of wearable early-warning systems, allowing coaches to manage training load proactively and prevent overuse injuries.

4.Discussion

This study demonstrates the efficacy of an integrated risk management framework for sports injuries, leveraging multimodal wearable data and advanced analytics in professional football. Our findings confirm that injury risk arises from the complex interplay between mechanical load, physiological state, and their interaction, rather than from isolated factors.

The strongest predictor was the Acute: Chronic Workload Ratio (ACWR), with a hazard ratio of 2.29. This finding strongly supports the established "training-injury prevention paradox" (Gabbett, 2016), where athletes needing high loads for adaptation become vulnerable to sudden spikes. The mean ACWR of the injured group (1.45) consistently exceeded the recognized risk threshold of 1.3 (Blanch & Gabbett, 2016), reinforcing its critical role in load management. A more nuanced discovery was the significant interaction between ACWR and skin temperature. While elevated skin temperature alone posed a moderate risk (HR=1.43), its combination with high ACWR exponentially increased injury probability. This suggests a physiological tipping point, where thermal stress (potentially indicating systemic inflammation or impaired recovery) reduces tissue tolerance to concurrent mechanical load, a synergy highlighted in integrated biophysical models (Chen & Dai, 2024; Tucker et al., 2021).

Furthermore, the deceleration rate (Dec_rate) emerged as a key independent biomechanical predictor, emphasizing the importance of monitoring movement quality and high-intensity mechanical events beyond overall volume (Rebelo et al., 2023). Conversely, higher heart rate variability (HRV-RMSSD) showed a protective effect (HR=0.76), aligning with literature linking robust parasympathetic activity to better recovery and lower injury risk (Gajda et al., 2024).

Among the machine learning models tested, XGBoost achieved superior performance (Accuracy=88%, AUC=0.94), likely due to its efficacy in capturing the non-linear interactions identified, such as that between ACWR and temperature. This aligns with trends in sports analytics favoring ensemble methods for tabular biomarker data (Claudino et al., 2022). Critically, SHAP analysis provided essential interpretability, identifying ACWR, Dec_rate, and Skin_temp as the most influential features. This moves beyond a "black-box" model, offering actionable insights for practitioners and fostering trust in AI-assisted decision support (Yang et al., 2024).

The practical translation of these insights is embodied in the proposed composite risk index and dashboard. This tool advocates for a multivariate risk boundary approach, where alerts are based on the co-occurrence of multiple risk factors (e.g., high ACWR + elevated skin temperature + low HRV), rather than isolated thresholds. This enables more precise, personalized interventions and bridges the gap between complex analytics and practical, real-time decision-making by coaches and medical staff, directly addressing the need for context-specific risk frameworks (Ju et al., 2023).

This study has limitations. The sample was specific to professional football, requiring external validation for other sports and populations. The observational period, though data-rich, may not capture seasonal variations, and unmeasured confounders like psychological stress could influence outcomes. Future research should focus on validating this model in independent cohorts, developing and testing real-time alert systems in controlled trials, and incorporating novel data streams from wearable biosensors for enhanced physiological profiling.

In conclusion, by integrating biomechanical and physiological monitoring via wearables, we can identify athletes at imminent injury risk with high accuracy. The developed XGBoost model and composite risk index provide a scalable, interpretable framework for proactive risk mitigation. This work paves the way for intelligent wearable systems that empower informed decisions, promoting safer and more sustainable athletic performance.

5.Conclusion

In conclusion, this study demonstrates that a data-driven, integrative approach is paramount for modern sports injury prevention. By simultaneously monitoring mechanical load (ACWR, decelerations), physiological status (temperature, HRV), and their interactions via WDDs, we can identify athletes at imminent risk with high accuracy. The developed XGBoost model and the composite risk index offer a scalable and interpretable framework for moving from retrospective data analysis to prospective risk mitigation. This work paves the way for the next generation of intelligent wearable systems that empower athletes and support staff to make informed decisions, ultimately fostering safer and more sustainable athletic performance.

In line with the discussed findings, this study comprehensively examined the integration of biomechanical, physiological, and environmental data obtained from wearable diagnostic devices (WDDs) to predict and manage sports injury risk among professional football players. By combining traditional statistical analyses with advanced machine learning algorithms, a multidimensional, data-driven framework for risk assessment and prevention was developed, bridging the gap between sensor technology, data analytics, and practical sports medicine applications. The findings revealed that the Acute: Chronic Workload Ratio (ACWR), Deceleration Rate (Dec_rate), and Skin Temperature (Skin_temp) were the most influential determinants of injury occurrence. Players whose ACWR exceeded 1.4 had more than twice the hazard of injury (HR = 2.29, $p < 0.001$), while each 0.5°C increase in skin temperature elevated the risk by approximately 43%. Higher deceleration rates (HR = 1.63, $p = 0.002$) were associated with increased mechanical loading and abrupt movement changes, further contributing to injury vulnerability. Conversely, higher Heart Rate Variability (HRV-RMSSD) values were protective (HR = 0.76, $p = 0.018$), reflecting improved autonomic recovery and reduced physiological fatigue.

Correlation analysis revealed a strong positive association between workload imbalance (ACWR, $r = 0.62$) and injury occurrence, alongside a moderate negative relationship between HRV-RMSSD ($r = –0.39$) and injury risk, highlighting the interplay between training load and physiological recovery in injury susceptibility. Among the predictive models, XGBoost achieved the best performance (Accuracy = 88%, AUC = 0.94), outperforming Random Forest and LSTM. SHAP analysis identified ACWR, Dec_rate, Acc_peak, and Skin_temp as the dominant predictors, explaining most of the model's variance. Simulation results further indicated that raising ACWR from 1.2 to 1.5 at 37.2°C nearly doubled the injury probability, with risks increasing sharply beyond 37.5°C—suggesting a physiological threshold beyond which recovery is impaired.

The integration of biomechanical and physiological indicators led to the development of a composite injury risk framework with an overall accuracy of about 86%, capable of identifying athletes in high-risk conditions. This model can be implemented in real-time monitoring systems to support proactive load management and personalized injury prevention. Overall, the study provides strong empirical evidence that imbalances between acute and chronic workloads, combined with physiological and thermal strain, substantially elevate the risk of musculoskeletal injury in professional football players. The proposed AI-assisted framework, based on the XGBoost algorithm, offers a robust and scalable foundation for data-driven risk management in sports. Future research should validate the model across other athletic disciplines and enhance adaptive algorithms for real-time application, paving the way toward next-generation intelligent wearable systems for safer and more sustainable athlete performance.

Reference

Chen, Z., & Dai, X. (2024). Utilizing AI and IoT technologies for identifying risk factors in sports. *Heliyon*, *10*(11). https://doi.org/10.1016/j.heliyon.2024.e32477.

Blanch, P., & Gabbett, T. J. (2016). *Has the athlete trained enough to return to play safely? The acute:chronic workload ratio permits clinicians to quantify a player's risk of subsequent injury.* British Journal of Sports Medicine, 50(8), 471-475. https://doi.org/10.1136/bjsports-2015-095445

Da Silva, L. (2024). Wearable technology in sports monitoring performance and health metrics. *Revista De Psicología Del Deporte (Journal of Sport Psychology)*, *33*(2), 250-258.

De Fazio, R., Mastronardi, V. M., De Vittorio, M., & Visconti, P. (2023). Wearable sensors and smart devices to monitor rehabilitation parameters and sports performance: An overview. *Sensors*, *23*(4), 1856. https://doi.org/10.3390/s23041856.

Fotiadis, D. I., Glaros, C., & Likas, A. (2006). Wearable medical devices. *Wiley encyclopedia of biomedical* engineering, *3*. https://doi.org/10.1002/9780471740360.ebs1326.

Gabbett, T. J. (2016). The training—injury prevention paradox: Should athletes be training smarter and harder? *British journal of sports medicine*, *50*(5), 273-280. DOI: 10.1136/bjsports-2015-095788.

Gajda, R., Gajda, J., Czuba, M., Knechtle, B., & Drygas, W. (2024). Sports heart monitors as reliable diagnostic tools for training control and detecting arrhythmias in professional and leisure-time endurance athletes: An expert consensus statement. *Sports medicine*, *54*(1), 1-21. DOI: 10.1007/s40279-023-01948-4.

Claudino, J. G., Capanema, D. O., de Souza, T. V., Serrão, J. C., Pereira, M. R., & Nassis, G. P. (2022). Current approaches to the use of artificial intelligence for injury risk assessment and performance prediction in team sports: a systematic review. Sports Medicine - Open, 8(1), 28. https://doi.org/10.1186/s40798-022-00420-3

Ju, F., Wang, Y., Yin, B., Zhao, M., Zhang, Y., Gong, Y., & Jiao, C. (2023). Microfluidic wearable devices for sports applications. *Micromachines*, *14*(9), 1792. https://doi.org/10.3390/mi14091792.

Kovoor, M., Durairaj, M., Karyakarte, M. S., Hussain, M. Z., Ashraf, M., & Maguluri, L. P. (2024). Sensor-enhanced wearables and automated analytics for injury prevention in sports. *Measurement: Sensors*, *32*, 101054. DOI:10.1016/j.measen.2024.101054.

Leckey, C., Van Dyk, N., Doherty, C., Lawlor, A., & Delahunt, E. (2025). Machine learning approaches to injury risk prediction in sport: A scoping review with evidence synthesis. *British Journal of Sports Medicine*, *59*(7), 491-500. DOI: 10.1136/bjsports-2024-108576.

McDevitt, S., Hernandez, H., Hicks, J., Lowell, R., Bentahaikt, H., Burch, R., ... & Anderson, B. (2022). Wearables for biomechanical performance optimization and risk assessment in industrial and sports applications. *Bioengineering*, *9*(1), 33. DOI: 10.3390/bioengineering9010033.

Musat, C. L., Mereuta, C., Nechita, A., Tutunaru, D., Voipan, A. E., Voipan, D., ... & Nechita, L. C. (2024). Diagnostic applications of AI in sports: A comprehensive review of injury risk prediction methods. *Diagnostics*, *14*(22), 2516. DOI: 10.3390/diagnostics14222516.

Ranavolo, A., Draicchio, F., Varrecchia, T., Silvetti, A., & Iavicoli, S. (2018). Wearable monitoring devices for biomechanical risk assessment at work: Current status and future challenges—A systematic review. *International journal of environmental research and public health*, *15*(9), 2001. https://doi.org/10.3390/ijerph15092001.

Rebelo, A., *Martinho*, D. V., Valente-dos-Santos, J., Coelho-e-Silva, M. J., & Teixeira, D. S. (2023). From data to action: A scoping review of wearable technologies and biomechanical assessments informing injury prevention strategies in sport. *BMC sports science, medicine and rehabilitation*, *15*(1), 169. DOI: 10.1186/s13102-023-00783-4.

Saliba, B. (2020). *The role of wearable technological devices in risk management for Maltese sports participants* (Master's thesis, University of Malta). https://www.um.edu.mt/library/oar/handle/123456789/67224.

Saliba, B., Spiteri, J., & Cortis, D. (2022). Insurance and wearables as tools in managing risk in sports: Determinants of technology take-up and propensity to insure and share data. *The Geneva Papers on Risk and Insurance-Issues and Practice*, *47*(3), 499-519. DOI: 10.1057/s41288-021-00250-6.

Seçkin, A. Ç., Ateş, B., & Seçkin, M. (2023). Review on wearable technology in sports: Concepts, challenges and opportunities. *Applied sciences*, *13*(18), 10399. https://doi.org/10.3390/app131810399.

Svempe, L. (2024). Exploring impediments imposed by the medical device regulation EU 2017/745 on software as a medical device. *JMIR Medical Informatics*, *12*(1), e58080. DOI: 10.2196/58080.

Tucker, R., Raftery, M., & Verhagen, E. (2021). Injury risk and a tackle ban in youth rugby union: reviewing the evidence and searching for targeted, effective interventions. A critical review. British Journal of Sports Medicine, 55(6), 321-328. https://doi.org/10.1136/bjsports-2020-102529

Van Vroonhoven, J. (2020). Risk management for medical devices and the new BS EN ISO 14971. ASM International.

Yang, L., Amin, O., & Shihada, B. (2024). Intelligent wearable systems: Opportunities and challenges in health and sports. *ACM Computing Surveys*, *56*(7), 1-42. https://doi.org/10.1145/3648469.

Zadeh, A., Taylor, D., Bertsos, M., Tillman, T., Nosoudi, N., & Bruce, S. (2021). Predicting sports injuries with wearable technology and data analysis. *Information Systems Frontiers*, *23*(4), 1023-1037. DOI: 10.1007/s10796-020-10018-3.