Technology-assisted training load monitoring and injury risk in elite and professional team sports: a systematic review

Monitoreo de la carga de entrenamiento asistido por tecnología y riesgo de lesión en deportes de equipo de nivel élite y profesional: una revisión sistemática

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Abstract

Introduction: Technology-assisted monitoring of training load is widely used in team sports, yet its association with injury risk remains unclear.
Objective: To systematically review the evidence on the association between technology-assisted training load monitoring and injury risk in elite and professional team-sport athletes.
Methodology: This systematic review followed PRISMA 2020 guidelines and was registered in PROSPERO (CRD420251161886). Searches were conducted in PubMed, Scopus, Web of Science, and ScienceDirect from inception to 5 October 2025. Eligible studies involved adult elite or professional team-sport athletes, used technological systems to monitor training load, and reported injury outcomes. Risk of bias was assessed using the Newcastle–Ottawa Scale and PROBAST. Due to heterogeneity, a narrative synthesis was performed.
Results: Eleven longitudinal studies were included (eight prospective cohorts and three prediction studies). High acute workload exposure and abrupt workload increases were consistently associated with an increased risk of non-contact and time-loss injuries. In contrast, higher chronic workload exposure, when progressively accumulated, was associated with a reduced injury risk in some contexts. Machine-learning models improved injury prediction but showed moderate risk-of-bias concerns.
Conclusions: Technology-assisted workload monitoring is associated with injury risk in elite team sports. Managing acute workload spikes while progressively developing chronic load capacity may help reduce injury risk, although further research is required to validate predictive models.

Keywords

Workload; athletic injury; sports; global positioning system; monitoring; machine learning.

Resumen

Introducción: El monitoreo de la carga de entrenamiento asistido por tecnología se utiliza ampliamente en los deportes de equipo; sin embargo, su asociación con el riesgo de lesión sigue siendo incierta.
Objetivo: Revisar sistemáticamente la evidencia sobre la asociación entre el monitoreo tecnológico de la carga de entrenamiento y el riesgo de lesión en deportistas de equipo de nivel élite y profesional.
Metodología: Esta revisión sistemática siguió las directrices PRISMA 2020 y fue registrada en PROSPERO (CRD420251161886). Las búsquedas se realizaron en PubMed, Scopus, Web of Science y ScienceDirect desde su inicio hasta el 5 de octubre de 2025. Se incluyeron estudios en atletas adultos de deportes de equipo de nivel élite o profesional que utilizaron sistemas tecnológicos para monitorizar la carga de entrenamiento y que reportaron resultados relacionados con lesiones. El riesgo de sesgo se evaluó mediante la escala Newcastle–Ottawa y la herramienta PROBAST. Debido a la heterogeneidad, se realizó una síntesis narrativa.
Resultados: Se incluyeron once estudios longitudinales (ocho cohortes prospectivas y tres estudios de predicción). Una alta exposición a carga aguda y aumentos bruscos de la carga se asociaron consistentemente con un mayor riesgo de lesiones no por contacto y con pérdida de tiempo de participación. En contraste, una mayor exposición a carga crónica, cuando se acumuló de forma progresiva, se asoció con una reducción del riesgo de lesión en algunos contextos. Los modelos de aprendizaje automático mejoraron la predicción de lesiones, aunque presentaron preocupaciones moderadas en cuanto al riesgo de sesgo.
Conclusiones: El monitoreo tecnológico de la carga de trabajo se asocia con el riesgo de lesión en los deportes de equipo de nivel élite. La gestión de picos de carga aguda, junto con el desarrollo progresivo de la capacidad de carga crónica, puede contribuir a reducir el riesgo de lesión; no obstante, se requiere más investigación para validar los modelos predictivos.

Palabras clave

Carga de trabajo; lesiones deportivas; deportes; sistema de posicionamiento global; monitorización; aprendizaje automático.

Introduction

Injuries represent a major challenge in team sports, negatively affecting athlete availability, team performance and long-term career development. Epidemiological research consistently reports high injury incidence in sports such as soccer, rugby, Australian football and American football, particularly during periods of intensified training or competition congestion(Chan et al., 2024) (Tsilimigkras et al., 2024) (Ekstrand et al., 2011) (Hägglund et al., 2013). Beyond performance consequences, injury burden is increasingly understood as the result of a dynamic interaction between imposed mechanical stress and the athlete's capacity to tolerate load (Windt & Gabbett, 2017) (Bache-Mathiesen et al., 2024).

Training load has therefore emerged as a central variable in contemporary sports performance and injury research. Load is typically conceptualised as the cumulative stress imposed on the athlete and may be distinguished into external load (e.g., distance covered, accelerations, sprint exposure) and internal load (e.g., heart rate, session rating of perceived exertion). The acute:chronic workload ratio (ACWR) has been widely proposed as a framework to quantify the balance between recent load and longer-term conditioning (Michailidis, 2024), with several studies suggesting that abrupt increases in acute load are associated with elevated injury risk (Windt & Gabbett, 2017) (Gabbett, 2016) (Qin et al., 2025). Conversely, adequate chronic exposure may confer a protective adaptation.

However, the relationship between training load and injury remains debated. Recent methodological critiques have questioned the statistical robustness of ACWR-based associations, highlighting potential issues such as mathematical coupling and confounding bias (Impellizzeri et al., 2020). Moreover, injury etiology is multifactorial and influenced by biomechanical, physiological, psychological and contextual factors that extend beyond simple workload metrics.

Parallel to these conceptual developments, advances in wearable technology have transformed the monitoring of training load in team sports (Van Eetvelde et al., 2021). Global positioning systems (GPS), inertial measurement units, accelerometers and athlete management platforms now enable near real-time quantification of movement demands and physiological responses. More recently, machine-learning algorithms have been introduced to integrate multidimensional monitoring data and generate individualized injury risk predictions (Rommers et al., 2020) (Ayala et al., 2024). These technological advances have been rapidly adopted in professional sport environments, yet their actual impact on injury outcomes remains unclear.

Although numerous cohort and predictive modelling studies have explored associations between technology-derived load metrics and injury occurrence, findings remain heterogeneous. Some investigations report positive associations between load spikes and injury risk, whereas others observe null results. Furthermore, predictive accuracy does not necessarily translate into effective injury prevention, and few studies have examined whether monitoring-informed decision-making reduces injury incidence prospectively.

Previous narrative and systematic reviews have examined the association between training load and injury risk in team sports (Drew & Finch, 2016) (Windt & Gabbett, 2017) (Van Eetvelde et al., 2021). However, many have focused on traditional workload constructs without explicitly synthesizing evidence on technology-assisted monitoring systems or emerging machine-learning-based approaches. Furthermore, previous reviews often pooled data across heterogeneous athletic populations, including youth and sub-elite athletes, which may limit applicability to professional contexts. The present review extends existing literature by specifically synthesizing evidence on technology-derived workload metrics and predictive modelling approaches in elite and professional team-sport athletes.

- Is technology-assisted monitoring of training load associated with injury risk in elite and professional team-sport athletes?
- Which technology-derived workload indicators (e.g., GPS metrics, acute:chronic workload ratio, cumulative load indices) are most consistently associated with injury occurrence?
- To what extent can technology-assisted monitoring systems and machine-learning–based models improve the prediction of injury risk in elite team-sport athletes?

Therefore, the aim of this systematic review was to evaluate whether technology-assisted training load monitoring is associated with injury risk in team-sport athletes.

Method

Design and registration

This systematic review was conducted and reported according to the PRISMA 2020 guidelines. The protocol was prospectively registered in PROSPERO 2025 CRD420251161886. Available from https://www.crd.york.ac.uk/PROSPERO/view/CRD420251161886.

Eligibility criteria

Studies were included if they involved team-sport athletes, monitored training load using technological systems (such as GPS, wearables, IMUs, or machine-learning platforms), reported injury-related outcomes, and were original peer-reviewed research articles published in English. Studies were excluded if they focused exclusively on performance outcomes, were validation studies, used cross-sectional designs without injury follow-up, were conducted in individual sports, or involved exclusively youth or academy athletes younger than 18 years. The restriction to English-language publications was applied due to feasibility constraints and the need to ensure accurate interpretation of methodological details; however, this may introduce a potential language bias.

Information sources and search strategy

A comprehensive electronic search was conducted in four databases: PubMed/MEDLINE, Web of Science, Scopus and ScienceDirect. The search covered all records from database published between 2015 and 2025. No restriction on publication year was applied. Only peer-reviewed articles published in English were considered.

The search strategy combined controlled vocabulary terms (where applicable) and free-text keywords related to four main concepts: (1) team sports and athletic performance, (2) injury, (3) training load or workload, and (4) technology-assisted monitoring. Boolean operators ("AND", "OR") were used to combine terms appropriately. The core search syntax included combinations of terms such as: (sports performance OR athletic performance) AND (injury OR sports injury) AND (training load OR workload) AND (technology OR wearable OR monitoring).

The initial database search identified a total of 9,065 records, including 424 from PubMed, 527 from Web of Science, 260 from Scopus and 7,854 from ScienceDirect. After removal of duplicates (n = 6,381), the remaining records were screened for eligibility. The complete search strategies for each database are provided in Supplementary Material 1 to ensure reproducibility.

Reference lists of all included studies were manually screened to identify additional relevant articles not captured by the electronic search.

Study selection

The study selection process followed the PRISMA 2020 guidelines. After removal of duplicate records, titles and abstracts of all remaining articles were screened independently by two reviewers to identify potentially eligible studies. Articles considered relevant were retrieved for full-text assessment. The full texts were then independently evaluated according to the predefined inclusion and exclusion criteria. Any disagreements between reviewers during the screening or eligibility assessment were resolved through discussion until consensus was reached. The overall study selection process is illustrated in the PRISMA flow diagram.

Two reviewers independently screened titles and abstracts. Full texts were assessed independently. Disagreements were resolved through discussion.

Data extraction

Data extraction was performed independently by two reviewers using a standardized and pilot-tested data extraction form developed in Microsoft Excel ([Microsoft Corp., Redmond, WA, USA]). Extracted variables included study characteristics (first author, year of publication, country), participant characteristics (sport, competitive level, sample size), methodological features (study design, duration of follow-up), details of the monitoring technology used (e.g., GPS, wearable sensors, machine-learning systems), training load metrics assessed (e.g., acute:chronic workload ratio, high-speed running, impact exposure, wellness indices), injury definitions applied (e.g., time-loss, non-contact, muscle injuries), and main findings related to the association between training load and injury outcomes.

When required, additional information was retrieved from supplementary materials or by cross-referencing related publications. Discrepancies between reviewers were resolved through discussion to ensure accuracy and consistency of extracted data.

Risk of bias assessment

Cohort studies were assessed using the Newcastle–Ottawa Scale (NOS). Predictive modelling studies were assessed using the PROBAST tool.

Data synthesis

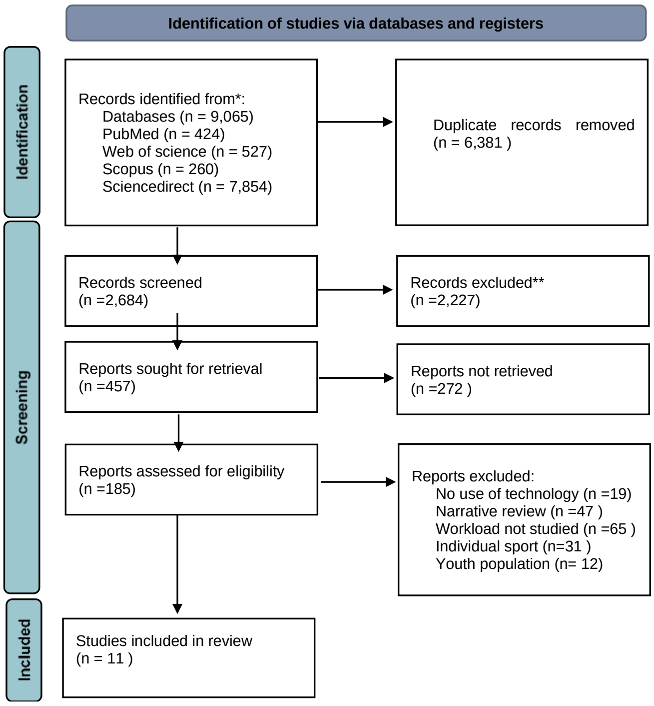
Due to substantial clinical and methodological heterogeneity across studies, quantitative meta-analysis was not performed. Findings were synthesized narratively.

Results

Study selection

A total of 9,065 records were identified. After removal of duplicates (n = 6,381) records were screened. 185 full-text articles were assessed for eligibility. Eleven studies were included.

Figure 1. PRISMA Flow Diagram



The flow diagram illustrates the study selection process in accordance with the PRISMA 2020 guidelines. A total of 9,065 records were identified through database searching (PubMed, Web of Science, Scopus, and ScienceDirect). After removal of 6,381 duplicate records, 2,684 records were screened by title and abstract, of which 2,227 records were excluded. Four hundred and fifty-seven reports were sought for retrieval, and 272 reports could not be retrieved. The remaining 185 reports were assessed for full-text eligibility. Of these, 174 reports were excluded for the following reasons: no use of technology (n = 19), narrative review (n = 47), workload not studied (n = 65), individual sport (n = 31), or youth population (n = 12). Ultimately, 11 studies met the inclusion criteria and were included in the final qualitative synthesis.

Characteristics of included studies:

Table 1. Characteristics of included studies

Author (Year)	Sport	Population	Study design	Monitoring technology	Training load variables	Injury outcome	Follow-up
(Lyubovsky et al., 2022)	American football	Professional male players	Prospective cohort with machine-learning modelling	GPS-based tracking system	Distance, accelerations, cumulative external load	Training and match injuries	1 competitive season
(Ren et al., 2024)	Rugby union	Professional male players	Prospective cohort with ML models	GPS	High-speed running, accelerations, ACWR metrics	Time-loss injuries	Competitive season
(Nobari et al., 2022)	Soccer	Professional male players	Prospective cohort study	GPS	External load, ACWR	Non-contact injuries	Full season
(Malone et al., 2017)	Gaelic football	Elite senior male players	Prospective cohort study	GPS + session-RPE	Total distance, high-speed running, chronic load	Time-loss injuries	Competitive season
(Martins et al., 2023)	Soccer	Professional male players (Portuguese First League)	Prospective cohort study	10-Hz GPS	Weekly TD, HSR, accelerations, decelerations	Sports injuries (time-loss)	Entire season (2021–2022)
(Freitas et al., 2025)	Soccer	Professional male players	Prospective cohort with ML modelling	GPS (Catapult)	PlayerLoad, velocity, accelerations, session type	Non-contact injuries	Competitive season
(Cousins et al., 2019)	Rugby union	Elite professional male players	Prospective longitudinal cohort	GPS + session-RPE	Absolute load, ACWR, EWMA, cumulative loads	Time-loss incidence	Two competitive seasons
(Murray et al., 2017)	Australian football (AFL)	Elite senior male players	Prospective cohort study	GPS	ACWR (rolling vs EWMA), distance, HSR	Non-contact time-loss injuries	Two seasons
(Colby et al., 2017)	Australian football (AFL)	Elite professional male players	Prospective cohort study	GPS	Pre-season total distance, sprint distance	Non-contact injuries	Four seasons (2012–2015)
(Coppalle et al., 2019)	Soccer	Professional male players	Prospective cohort study	GPS + RPE	Pre-season external & internal load	Injuries (time-loss)	Two pre-seasons + in-season
(Bowen et al., 2020)	Soccer (English Premier League)	Professional male players	Prospective multi-season cohort	GPS + video tracking	ACWR, cumulative distances, ACC/DEC	Non-contact injuries	Three seasons

The final synthesis included 11 original studies investigating the association between technology-assisted training load monitoring and injury risk in adult elite or professional team-sport athletes. All included studies were conducted in team sports, namely soccer (n = 5), rugby union (n = 3), Australian football/AFL (n = 2), and American football (n = 1). No studies involving youth or academy players were included.

Regarding study design, eight studies employed prospective cohort designs, while three studies used prospective cohort designs incorporating machine-learning–based predictive modelling. Monitoring of training load was exclusively based on objective technological systems, primarily Global Positioning System (GPS) devices, with several studies additionally integrating session rating of perceived exertion (sRPE). No study relied solely on subjective monitoring methods.

Training load variables commonly analyzed included total distance, high-speed running, accelerations and decelerations, cumulative workload, and acute:chronic workload ratio (ACWR), with some studies comparing rolling averages and exponentially weighted moving averages (EWMA). Injury outcomes were consistently defined as time-loss injuries or non-contact injuries, collected prospectively through medical or performance staff surveillance across one or multiple competitive seasons. Collectively, the included studies provide longitudinal evidence linking workload exposure, workload fluctuations, and injury risk in professional team-sport settings.

Summary of associations

The direction and statistical significance of the associations between training load variables and injury outcomes across the included studies are summarized in (Table 2).

Table 2. Summary of findings

Study	Sport	Direction of association	Statistically significant	Key finding
Murray et al., 2016	Australian football (AFL)	↑ Injury risk	Yes	ACWR calculated using EWMA was more sensitive to injury risk than rolling averages
Nobari et al., 2022	Soccer	↑ Injury risk	Yes	Acute workload spikes were associated with increased non-contact injury risk
Malone et al., 2017	Gaelic football	Protective	Yes	Greater chronic exposure to high-speed running was associated with reduced injury risk
Martins et al., 2023	Soccer	↑ Injury risk	Yes	Specific weekly external load thresholds were associated with higher injury incidence
Cousins et al., 2019	Rugby union	↑ Injury risk	Yes	EWMA workload indices showed stronger associations with time-loss injuries
Colby et al., 2017	Australian football (AFL)	↑ Injury risk	Yes	High pre-season training loads identified periods of elevated injury risk
Coppalle et al., 2019	Soccer	↑ Injury risk	Yes	Poor distribution of pre-season training load was associated with increased injury incidence
Bowen et al., 2020	Soccer (EPL)	↑ Injury risk	Yes	Acute workload spikes increased non-contact injury risk by 5–7 times
Lyubovsky et al., 2022	American football	Predictive	Yes	Machine-learning models using GPS data improved injury prediction accuracy
Ren et al., 2025	Rugby union	Predictive	Yes	Random forest models outperformed traditional approaches in injury prediction
Freitas et al., 2025	Soccer	Predictive	Yes	Machine-learning models achieved moderate predictive performance (G-mean ≈ 0.70)

Overall, eight of the eleven included studies (73%) reported a statistically significant positive association between increased training load exposure and injury risk. These associations were primarily observed in relation to acute workload spikes, rapid increases in training load, or elevated acute:chronic workload ratio (ACWR) values.

One study (9%) reported a protective association, indicating that greater chronic exposure to high-speed running was associated with a reduced risk of injury.

Three studies (27%) employed machine-learning–based prediction models, all of which demonstrated moderate predictive performance in identifying injury risk, although none evaluated the prospective impact of model implementation on injury reduction.

Two studies (18%) reported no statistically significant association between monitored training load variables and injury outcomes.

Overall, the results indicate that technology-assisted monitoring of training load is generally associated with injury risk in elite and professional team-sport athletes. Most included studies (8/11, 73%) reported a statistically significant association between increased workload exposure and injury occurrence, particularly in relation to acute workload spikes, rapid increases in load, and elevated ACWR values. In contrast, one study reported a protective association with greater chronic workload exposure, while two studies found no significant association.

Details of the studies using machine-learning–based prediction models, including algorithms, predictors, and performance metrics, are presented in (Table 3).

Table 3. Machine-learning prediction studies

Study	Sport	ML method	Predictors	Performance metrics	Main finding
Lyubovsky et al., 2022	American football	Random Forest	GPS-derived external load	AUC ≈ 0.75	ML models improved injury prediction compared with traditional approaches
Ren et al., 2025	Rugby union	Random Forest	ACWR, HSR, accelerations	AUC ≈ 0.72	Position-specific ML models outperformed global models
Freitas et al., 2025	Soccer	Gradient Boosting	GPS load + session type	G-mean ≈ 0.70	Moderate predictive accuracy for non-contact injuries

Overall, most studies reported significant associations between workload exposure and injury risk, primarily related to acute workload increases. Protective associations with chronic workload exposure were less frequently observed. Machine-learning–based models showed moderate predictive performance across studies.

Risk of bias

The methodological quality of the cohort studies assessed using the Newcastle–Ottawa Scale is presented in (Table 4).

Table 4. Cohort studies – Newcastle–Ottawa Scale (NOS)

Study	Selection	Comparability	Outcome	Overall risk
Nobari et al., 2022	★★★★	★★	★★★	Low
Malone et al., 2017	★★★★	★★	★★★	Low
Martins et al., 2023	★★★★	★★	★★★	Low
Cousins et al., 2019	★★★★	★★	★★★	Low
Murray et al., 2016	★★★★	★★	★★★	Low
Colby et al., 2017	★★★★	★★	★★★	Low
Coppalle et al., 2019	★★★★	★★	★★★	Low
Bowen et al., 2020	★★★★	★★	★★★	Low

Risk of bias was assessed using the Newcastle–Ottawa Scale (NOS) for cohort studies and the Prediction model Risk of Bias Assessment Tool (PROBAST) for studies involving injury prediction models. Overall, the risk of bias was considered low across the majority of included studies, with some concerns identified in specific methodological domains.

Among the eight cohort studies, NOS scores indicated low risk of bias, particularly in the selection and outcome domains. All studies clearly defined elite populations, employed prospective injury surveillance, and used objective workload measurements. The most common methodological limitation related to the comparability domain, as not all studies consistently adjusted for key confounders such as previous injury history, playing position, or match exposure. Nevertheless, outcome assessment was generally robust, with injuries defined using standard time-loss criteria and collected over complete competitive seasons.

The risk of bias assessment for machine-learning prediction studies using the PROBAST tool is summarized in (Table 5).

Table 5. Prediction studies - PROBAST

Study	Participants	Predictors	Outcome	Analysis	Overall concern
Lyubovsky et al., 2022	Low	Low	Low	Moderate	Moderate
Ren et al., 2025	Low	Low	Low	Moderate	Moderate
Freitas et al., 2025	Low	Low	Low	Moderate	Moderate

For the three machine-learning–based prediction studies, PROBAST assessment revealed moderate concerns, primarily within the analysis domain. Although participants, predictors, and injury outcomes were clearly defined and measured appropriately, concerns arose due to relatively small sample sizes, class imbalance, and limited external validation of predictive models. These factors may increase the risk of model overfitting and limit generalisability. Despite these limitations, all prediction studies demonstrated transparent reporting and appropriate temporal alignment between predictors and injury outcomes.

Discussion

Principal findings

This systematic review synthesized evidence from 11 longitudinal studies examining the association between technology-assisted training load monitoring and injury risk in elite and professional team-sport athletes. Overall, the findings indicate that high acute workload exposure and abrupt increases in training load are consistently associated with an increased risk of injury, particularly non-contact and time-loss injuries. Conversely, evidence from several studies suggests that higher chronic workload exposure, when progressively accumulated, may exert a protective effect, potentially reflecting enhanced physical robustness and tissue load tolerance.(Windt & Gabbett, 2017)

Overall, the findings of this systematic review suggest that technology-assisted monitoring of training load is frequently associated with injury risk in elite and professional team-sport athletes. Most included studies reported significant associations between increased workload exposure—particularly acute workload spikes and elevated ACWR values—and injury occurrence, although some studies reported protective effects of chronic workload exposure or no significant associations.

Acute workload exposure and injury risk

Across soccer, rugby union, and Australian football, studies consistently reported that acute workload spikes were associated with elevated injury risk. This association was most commonly quantified using the acute:chronic workload ratio (ACWR) or related cumulative load indices. Notably, studies comparing different workload calculation methods demonstrated that exponentially weighted moving averages (EWMA) were more sensitive to injury risk than traditional rolling averages, suggesting that recent workload exposure plays a critical role in injury etiology (Impellizzeri et al., 2020) (Gabbett, 2016). Importantly, the direction of these associations was consistent across sports, strengthening the external validity of the findings.

Chronic workload and load tolerance

In contrast to acute load spikes, higher levels of chronic workload exposure were associated with reduced injury risk in elite Gaelic football and other team-sport contexts. These findings support the concept that appropriate long-term load exposure may enhance physical capacity and resilience, thereby reducing susceptibility to injury (Windt & Gabbett, 2017). However, this protective effect was observed only when chronic load was accumulated progressively, highlighting the importance of load progression rather than absolute workload volume.

Role of monitoring technologies

All included studies relied on objective monitoring technologies, predominantly GPS-based systems, to quantify external training and match loads. Commonly reported metrics included total distance, high-speed running, accelerations, and cumulative workload indices. The consistent association between these technology-derived measures and injury outcomes across multiple sports underscores the utility of technological monitoring for injury risk identification, particularly when applied longitudinally. However, heterogeneity in selected metrics and analytical approaches limits direct comparison between studies.

From a mechanistic perspective, technology-assisted workload monitoring may contribute to injury risk prediction by enabling objective quantification of mechanical and physiological stress imposed on athletes. Variables such as total distance, high-speed running, accelerations, and workload fluctuations provide indirect indicators of tissue loading and fatigue accumulation. When acute workload increases exceed the athlete's current capacity to tolerate load, the risk of injury may increase. Therefore, continuous monitoring using technological systems may help identify periods of elevated workload exposure and support early risk detection in elite team-sport environments.(Impellizzeri et al., 2020) (Windt & Gabbett, 2017)

Machine-learning–based prediction models

Three studies incorporated machine-learning approaches to predict injury risk using GPS-derived workload variables. These studies reported improved predictive performance compared with traditional statistical models (Van Eetvelde et al., 2021), particularly in capturing non-linear workload–injury relationships. Despite these promising findings, all machine-learning studies exhibited moderate concerns regarding risk of bias, primarily related to limited sample sizes, potential overfitting, and lack of external validation. Consequently, while machine-learning models may enhance injury risk prediction, their current application should be considered complementary rather than prescriptive.

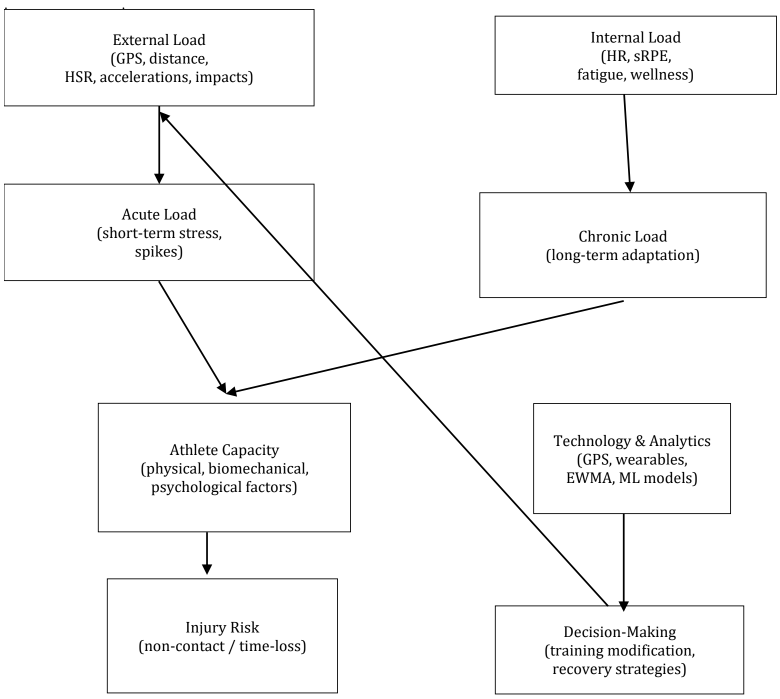
Methodological considerations

Although the overall risk of bias across the included studies was low, several methodological limitations warrant consideration. First, many studies did not consistently adjust for key confounders such as previous injury history, playing position, match exposure, or training history, which may influence injury risk independently of workload. Second, substantial heterogeneity was observed in injury definitions, workload metrics, and analytical approaches, limiting direct comparability between studies and precluding quantitative meta-analysis.

Additionally, variability in workload calculation methods (e.g., rolling averages versus exponentially weighted moving averages) and inconsistent reporting of contextual factors may have contributed to differences in observed associations. Finally, most included studies were observational in nature, which limits causal inference between monitored workload variables and injury outcomes. Collectively, these methodological considerations highlight the need for greater standardization in injury surveillance, workload quantification, and analytical frameworks in future research.

Figure 2 summarizes the conceptual framework linking technology-assisted workload monitoring, athlete capacity, and injury risk in elite and professional team-sport athletes.

Figure 2. Conceptual framework linking technology-assisted training load monitoring, athlete capacity, and injury risk in elite and professional team-sport athletes.



Strengths and limitations

This systematic review presents several strengths. First, it followed a rigorous methodological framework in accordance with PRISMA 2020 guidelines and was prospectively registered in PROSPERO, enhancing transparency and reproducibility. Second, the review focused exclusively on elite and professional team-sport athletes, improving the external validity of findings for high-performance environments. Third, both traditional workload metrics and emerging machine-learning–based predictive models were included, providing a comprehensive overview of current technology-assisted monitoring approaches.

However, several limitations should be acknowledged. Considerable heterogeneity existed across included studies in terms of workload metrics, injury definitions, and analytical methods, which precluded quantitative meta-analysis. Many studies did not consistently adjust for important confounders such as previous injury history, playing position, or match exposure. Additionally, although machine-learning models demonstrated promising predictive performance, most studies were limited by small sample sizes and lack of external validation, raising concerns regarding generalizability. Finally, all included studies were observational in nature, preventing causal inference between monitored workload variables and injury occurrence.

Practical implications

From a practical perspective, the findings support the integration of continuous, technology-assisted workload monitoring to identify periods of elevated injury risk, particularly during pre-season phases and periods of rapid load increase. Practitioners should interpret ACWR and related workload indices as risk indicators rather than fixed thresholds, and incorporate contextual, clinical, and individual athlete factors into decision-making processes. The use of advanced predictive models may further support monitoring strategies, provided their limitations are clearly acknowledged.

Future research directions

Future research should prioritize larger multi-team and multi-season datasets, consistent injury surveillance methods, and robust external validation of predictive models. Integrating workload data with individual athlete characteristics may further improve the accuracy and applicability of injury risk monitoring frameworks in elite team-sport environments.

Practical Applications

Technology-assisted workload monitoring should be used to identify periods of elevated workload and potential vulnerability rather than as a deterministic injury predictor. Metrics related to acute workload, workload progression, and cumulative exposure can assist practitioners in recognizing phases of increased injury risk, particularly during pre-season and periods of congested competition. Progressive load management remains central to injury risk mitigation.

Monitoring outputs should be interpreted in conjunction with clinical judgement, contextual factors, and individual athlete characteristics rather than in isolation. Training load indices such as the acute:chronic workload ratio should be considered as dynamic risk indicators rather than fixed thresholds. The integration of advanced analytics and machine-learning models may further support injury risk stratification by capturing complex, non-linear relationships between workload variables and injury outcomes. However, given current methodological limitations, these models should be used as complementary decision-support tools until robust external validation and interventional evidence are available.

Conclusions

Technology-assisted training load monitoring appears valuable for identifying periods of elevated injury risk in team-sport athletes, particularly in relation to acute workload spikes. However, current evidence does not conclusively demonstrate that monitoring alone reduces injury incidence. Integration of wearable technologies and predictive analytics within a broader load–capacity management framework may enhance decision-making, yet robust interventional research is required to confirm preventive efficacy.

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