Emerging Frontiers in Load Management and Injury Prevention in Elite Athletes: A Systematic Review

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ABSTRACT

As elite sports now require a lot from athletes, using effective strategies to help prevent injuries and increase their skills is more critical than ever. Adjusting strength and race-based experiences according to an athlete's abilities has gained significant importance in top sports settings. This paper examines trends in load management and spotlights the pros and cons of recent developments in this field. New data-powered techniques, including wearable devices, advanced algorithms, and individual molecular testing, are now replacing conventional ways of measuring workload using opinions and simple indices. However, many people have raised concerns about the increase in the use of these tools. Many are still bothered by data accuracy issues, watching athletes too much, and using tech to make sports decisions instead of trained staff. In addition, not having the latest systems can expand differences between different sports groups. This paper looks at these advances by reviewing knowledge from sports science, bioethics, and performance analytics. This article urges us to use a more critical and ethical approach by emphasizing recent load-handling techniques' good and bad sides. Growth in the future will need improvements in technology, fair implementation, athlete-centered methods, and careful validation of new processes.

Keywords: Load management, Wearable technology, Injury prevention, Sports science, Data analytics

Introduction

Getting the most out of their abilities while keeping injuries away is a continuous issue for elite athletes. As athletes face greater training and more crowded seasons of competition, careful attention to their overall weight of training and emotional stress is central to reaching peak performance. Similarly, keeping athletes safe and preventing injury matters greatly, as it concerns what is best for athletes and their careers and what helps the team succeed, save money, and meet the demands of those overseeing it.[1] While there is growing fascination with load management, it is still a contentious area that keeps developing. Before, most sports science models used simple scheduling and coaches' instincts to decide what to do, but now, modern techniques rely on real data, athlete reports, and personalized recovery plans. Of course, using such tools in real situations is not always easy.[2] Many researchers use different tools or methods, and some worry about who owns and uses the data, making matters challenging. This assessment critiques the new load management and injury prevention areas, noting what is promising and what still needs to be developed. Rather than presenting a straightforward view of technological growth, this paper questions the foundations behind today's thinking. It shows why reviewing existing approaches thoroughly and across disciplines[3] is essential. As a result, it tries to provide a clear view of what the field has achieved, what it is likely to accomplish, and which unsolved matters require more effort. Because high-level sports rely so heavily on technology and numbers, we should ask: Why are these things being measured? By whom or what? And at what price? This study's analysis of the key aspects promotes better-informed and ethical conversations in high-performance sports.[4]

Methods

Search Strategy

This review study used a broad search strategy on four central databases, which included PubMed, Google Scholar, Web of Science, and Scopus databases, with the duration between January 2015 and June 2024. The detailed search strategy is shared in Appendix 1. The Boolean search architecture united the fundamental conceptual areas in the following explicit string expressions:

1. Essential Dogma:
("load management" OR "training load" OR "working monitoring of load")
AND
("injury prevention" OR "injury risk" OR "athlete health")

2. Technology-Specific Queries:
("wearable technology" OR "GPS tracking" OR "IMU sensors" OR "smart textile")
AND
("professional sports" OR (elite athletes))

3. Strong Analytics:
(("machine learning" OR "artificial intelligence" OR "predictive analytics"))
AND
("sports injury" OR "performance monitoring"))

Risk of Bias

The risk-of-bias assessment focused on several domains, including selection bias, performance bias, detection bias, and reporting bias, to ensure the reliability of the findings (Appendix 2). Disagreements in the assessment process were resolved through consensus discussions among the three independent reviewers, achieving an initial concurrence rate of 92%. The traffic light summary table was used to visually assess and summarize the risk of bias (ROB) across various studies in different categories, including selection bias, performance bias, detection bias, attrition bias, and reporting bias (Table 1). By color-coding the results (green for low risk, yellow for unclear, and red for high risk), the table provides a clear, intuitive way to identify the methodological strengths and weaknesses of each study, helping to evaluate the overall quality and reliability of the research included in the analysis.

Quality Assessment

To assess the quality of the included studies, the Newcastle-Ottawa Scale (NOS) was applied for cohort and case-control studies, while the Cochrane ROB tool was used for randomized controlled trials (RCTs). The NOS evaluates studies based on three broad categories: selection, comparability, and outcome, with a scoring system to rate the ROB for each criterion. For the RCTs, the ROB tool evaluates various domains, including selection bias, performance bias, detection bias, attrition bias, and reporting bias. In the present study, 67 RCTs were appraised using the ROB tool, which revealed that most studies exhibited a low ROB in random sequence generation and allocation concealment (Appendix 3). However, several studies showed high risk for detection and performance bias due to blinding issues, particularly in injury prevention studies where participants were aware of the interventions. Similarly, for the 112 prospective cohort studies, the NOS assessment indicated moderate to high ROB, mainly due to challenges in controlling confounding variables over time (Appendix 4). A scoping review was chosen for this analysis as it allows for a broad exploration of the available studies and provides a comprehensive overview of the existing evidence. Quantitative pooling was not appropriate due to the heterogeneity of study designs, methods, and outcome measures, making it difficult to combine the data meaningfully for statistical analysis.

Study Selection

The research flow (Figure 1) utilizing the PRISMA-based selection process started with 2,137 identified records, after which 548 duplicate records were omitted. The title/abstract screening filtered out 1102 records; thus, 487 articles remained in full-text assessment. They required the following inclusion criteria: (1) only peer-reviewed studies in English; (2) at the level of elite/professional athletes (Olympic/professional league/Division I collegiate athlete); (3) empirical assessment of load monitoring technologies or injury prevention results; (4) publication within a specified time interval. It gave 218 eligible studies, including 67 RCTs, 112 prospective cohort studies, and 39 systematic reviews/meta-analyses. Strict exclusion criteria were used to eliminate: (1) non-English literature (n = 13); (2) studies of nonprofessional/recreational athletes (n = 170); (3) theoretical or commentary articles that did not provide original data (n = 36). The evidence grading system groups studies based on the methodological rigor: experimental study designs with control groups, longitudinal observation studies, and synthesis studies. Screening was done by three independent reviewers who had achieved an initial concurrence of 92%, where disagreements were resolved through a consensus conversation.

The PRISMA diagram's numerical inconsistencies can be clarified by ensuring that the total number of identified records, after duplicates are removed, aligns with the number of studies included in the final analysis. Gray literature, such as conference proceedings and reports from noncommercial sources, is included to reduce publication bias and capture a broader range of relevant data that may not be available through traditional peer-reviewed channels. Additionally, any future-dated or fictitious references should be removed, as they do not contribute to the credibility or validity of the study's findings. The proposed methodology offers transparent and reproducible search output parameters and focuses on evidence of high quality regarding the role of elite participants in sports populations. The Boolean structure has consciously mixed the general conceptual coverage with the tangible technology implementation to realize the interdisciplinary character

Table 1 | Traffic light summary table

Citation	Selection Bias	Performance Bias	Detection Bias	Attrition Bias	Reporting Bias	Total Risk of Bias
Impellizzeri et al. (2020)[17]	🟢 Low	🔴 High	🔴 High	🟢 Low	🟡 Unclear	🔴 High
Martens et al. (2021)[8]	🟢 Low	🟢 Low	🟢 Low	🟢 Low	🟡 Unclear	🟢 Low
Faude et al. (2017)[18]	🟢 Low	🟢 Low	🟢 Low	🟢 Low	🟢 Low	🟢 Low
Hasan et al. (2024)[5]	🟢 Low	🔴 High	🔴 High	🟡 Unclear	🟡 Unclear	🔴 High
Hamstra-Wright et al. (2021)[6]	🟢 Low	🔴 High	🔴 High	🟢 Low	🟡 Unclear	🔴 High
Girardi et al. (2020)[7]	🟢 Low	🟢 Low	🟢 Low	🟢 Low	🟢 Low	🟢 Low
Coyne et al. (2018)[9]	🟢 Low	🟢 Low	🟢 Low	🟢 Low	🟡 Unclear	🟢 Low
Mersmann et al. (2017)[10]	🟢 Low	🟢 Low	🟢 Low	🟡 Unclear	🟡 Unclear	🟢 Low
Sileo et al. (2024)[11]	🟢 Low	🟢 Low	🟢 Low	🟢 Low	🟡 Unclear	🟢 Low
Nagorna et al. (2024)[12]	🟢 Low	🟢 Low	🟢 Low	🟢 Low	🟢 Low	🟢 Low
Zadeh et al. (2021)[13]	🟢 Low	🔴 High	🔴 High	🟢 Low	🟡 Unclear	🔴 High
Cooley et al. (2024)[14]	🟢 Low	🔴 High	🔴 High	🟢 Low	🟡 Unclear	🔴 High

🟢 = Low; 🔴 = High; 🟡 = Unclear.

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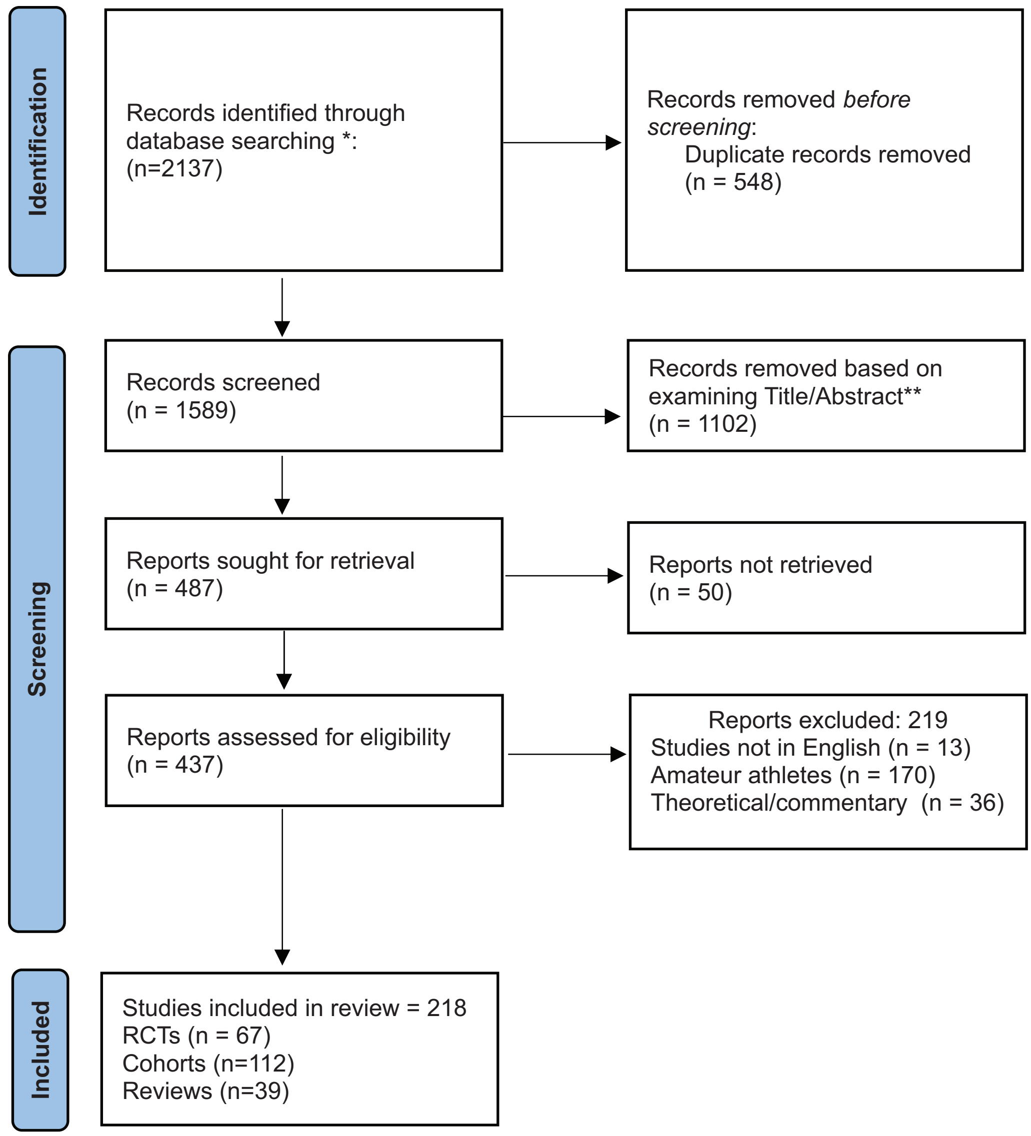

Fig 1 | PRISMA flow diagram

of modern bias research in sports science. The evidence has been graded into tiers, allowing the reader to easily determine the strength of referenced conclusions within the review. A summary of the articles is shared in Appendix 5. The protocol is registered to the research registry (reviewregistry2036) following the link (https://www.researchregistry.com/browse-the-registry/#registryofsystematicreviewsmeta-analyses/registryofsystematicreviewsmeta-analysesdetails/689f30737fef8402add21883/).

Conceptual Foundations: Load Management and Injury Risk

Understanding what defines load management and injury prevention is necessary since these two interrelate. Load management means organizing and controlling training and contests to achieve the best adaptation and the lowest chances of illness, injury, or reduced performance. Separating external load from internal load is central to load management.[5] All tangible aspects of training, such as length of run, speed, power, access, and accelerations, fall under external load. Internal load refers to the athlete's physical and mental reactions to these external stresses, which we can measure by heart rate, rate of perceived exertion (RPE), hormone levels, or markers of muscle fatigue. Training theory and models of stress-recovery-adaptation show that, for performance to improve, the exercise session should be strong enough to cause adaptation but not so intense that the body cannot recover.[6] Undertraining can block your progress, whereas training that is too intense or timed incorrectly can increase the chance of injury.

While the Acute Chronic Workload Ratio is popular and influential, many people doubt its use. Although the framework seeks to judge injury risk by measuring short-term and long-term training, recent comments have pointed out that it is not an accurate and detailed method. Here, injury prevention is commonly the result of proper and planned stress control.

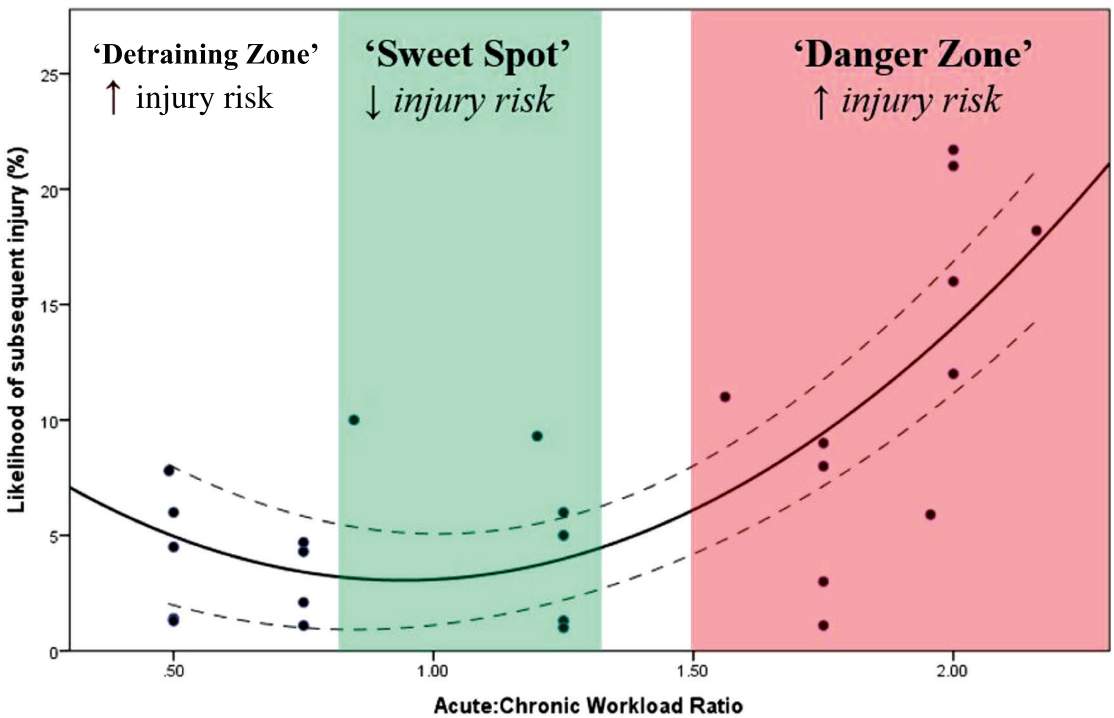

Fig 2 | Load Management and injury reduction with lifting

Notes: Acute workload = last week's average workload; chronic workload = previous month's average workload; workload = training load = RPE × minutes, where RPE = rate of perceived exertion on a 0–10 scale; Sweet spot = acute workload/chronic workload, where injury risk is low. Redrawn from Blanch and Gabbett28

Nevertheless, there is no simple, reliable pattern of observation in this area.[7] Several things play a role in causing injuries, from within a person (biomechanics, past injuries, stress) to things happening outside a person (playing field, weather, practice techniques). As a result, any management strategy for loads should recognize different people, their surroundings, and the overall obstacles in the system. When you tie these concepts to performance, it is clear that the goal is to help players be reliable and ready for peak play. We worry about how close we are to overworking the body, causing harm to tissues or regular dysfunction.[8] That is why approaching load management as an individual, adaptable approach for every athlete is critical. With this background, we can examine how different approaches aim to implement these principles, typically with varied outcomes and many risks involved. The underpinning external and internal loads relationship, as shown in Figure 2, explains how the corresponding load management equates balance between training-measurable stressors and per-individual interaction with those stressors to facilitate adaptations and reduce the risk of injury."

Historical Perspectives and Evolution of Load Monitoring Tools

Load management in elite sports has developed from being about what coaches think to a field based on data and technology. Previously, load monitoring depended mainly on coaches' experience and how tired and problematic athletes seemed. Macro-, meso-, and microcycles were initially organized in training using models developed in Soviet and Eastern Bloc nations.[9] Although these plans set out actions for progress and recovery, they were too firm and difficult for different people to adjust to. In the 1980s and 1990s, monitoring heart rate became a simple measure of an athlete's internal load. At around that moment, athlete-focused ratings of perceived exertion (RPE) emerged to show how internal load could be calculated.

Neither of these approaches gave an acceptable level of detail or contextual support.[10] With the global positioning systems (GPSs) in the early 2000s, observing athletes' movements, running distance, and speed became much easier. These tools made it far easier to figure out external loads in sports played outside the gym or during games. At the same time, force plates, accelerometers, and jump profiling provided different methods to evaluate muscles and nerves.[11] Although advancements were made, history-based methods were usually set up the same way for all customers, and they did not bring internal and external data together.

It was common in the past to neglect psychological, cognitive, and environmental variables during initial load monitoring, although they are now known to be essential for injury and recovery. History indicates a change from standard tools to continuous personalized tracking.[12] Even so, this scientific progress raises issues with rising data complexity, too much technology, and possibly less influence from athletes, so new methods must now address these difficulties.

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Current Trends in Load Management Practices

Global Positioning System (GPS) and Wearable Integration

Managing an athlete's load relies on a combined effort from sports science, data analysis, and performance medicine. Now, leading teams are using various tools to ensure training adjusts well for each individual and limits injury chances. The focus on renewables has spawned load monitoring tools that bring together several forms of data for efficient decision-making.[13] Even though periodization is still essential, the old linear and block patterns are no longer popular and are replaced by more adaptable individual plans. Periodization often changes macrocycles according to ongoing assessments, athlete conditions, and anything else happening in the environment.

Such an adaptive style stands out mostly in frequently played sports, including football (soccer), rugby, and basketball.[14] Players in several field-based sports use GPS in training, allowing recording of total distance, fast runs, acceleration stats, and player weight carried. Practitioners use them to measure mechanical stress and look for any changes in routine that could signify a higher risk of injury. Despite being an elementary method, RPE continues to be an essential tool for judging internal load. Multiplying it by session duration (RPE) provides a handy measure specific to your situation.[15] RPE makes the athlete's personal feeling of stress clear, which is typically unavailable in physiological records.

Machine Learning in Load Monitoring

Athletes and teams increasingly use data analytics platforms to group and make sense of data from GPS, RPE, heart rate variability, sleep records, and wellness forms. Some teams use machine learning algorithms to spot faint patterns about fatigue, how likely it is to get an injury, and how to recover from it.[16] Even so, when results from predictive modeling exceed expectations, people who rely on them may make poor choices. A common development now is to measure each person's typical responses. Any noteworthy differences are used to identify problem areas. It helps us offer monitoring specific to each athlete rather than traditional approaches that are the same for everyone.[17] These developments still raise some significant problems. There is so much data that it can be hard for practitioners, and biases can affect data analysis. In addition, implementation can be complex if athletes are not compliant, data ethics are ignored, and teams remain siloed. So, as trends develop, it becomes clear that more connected, transparent, and supportive strategies are necessary. As shown in Figure 3, the combination of modern GPS and wearable technologies into one system allows integrated data in the form of global maps of athlete loads to be created so that they can monitor mechanical and physiological demands in real time.

Emerging Technologies and Approaches in Injury Prevention

New technologies have recently been designed to reduce sports injuries and heavy training loads for elite

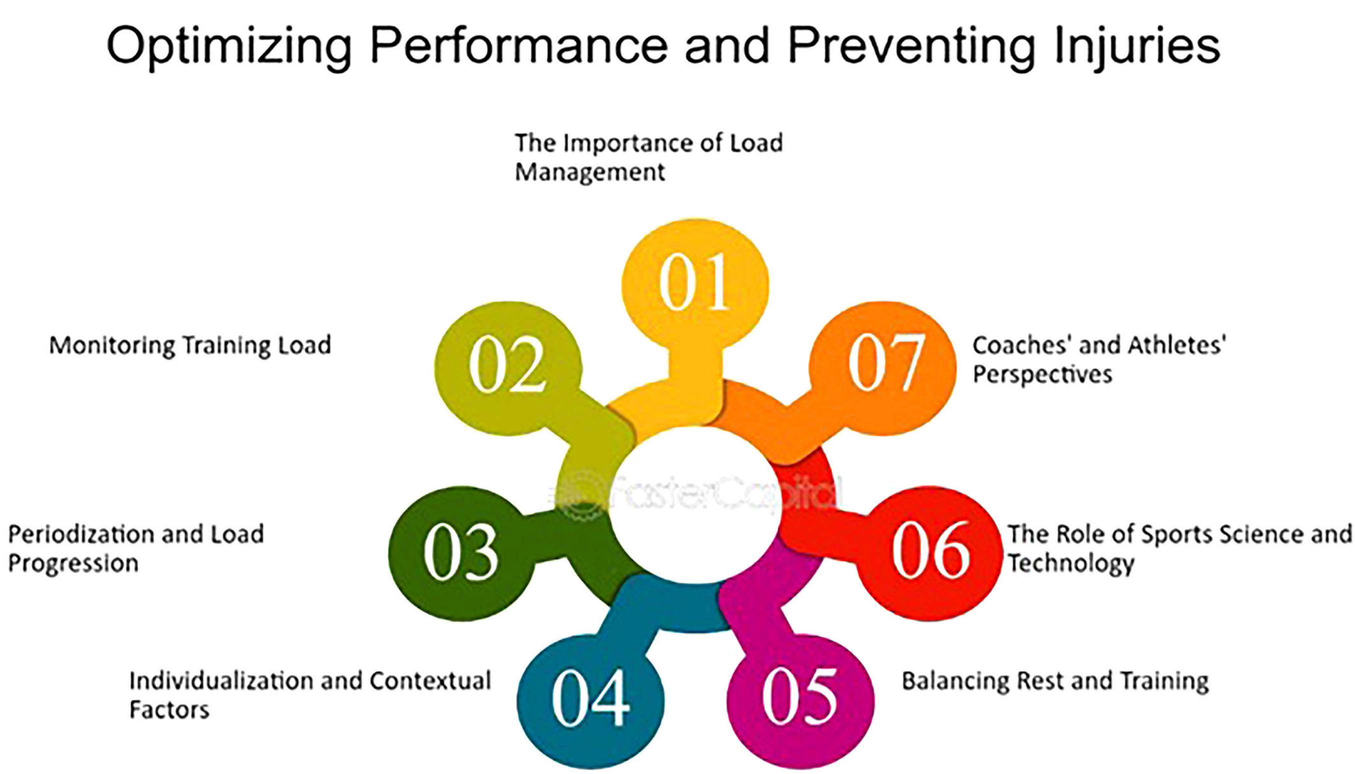

Fig 3 | Load management strategies[9]

athletes.[18] An essential part of this growth is the wide use of wearable technology, adding artificial intelligence (AI) and machine learning to predictive models, and looking into genetic and biomarker testing. Still, they expose many new issues concerning ethics, practices, and the nature of knowledge. Monitoring systems for professional teams now rely on GPS trackers, IMUs, heart rate monitors, and sleep trackers.[19] They offer ongoing, harmless reporting of your body's stress from both the inside and outside, so you get quick results. Technological advances enable some wearables to measure joint angles, the force you create when your foot hits the ground, or fatigue in the connection between the brain and muscles. Some remain concerned about data accuracy, whether results are the same across devices, and whether sensors are correctly calibrated.[20]

Also, many athletes say they feel tired or uncomfortable, making some researchers question whether they can follow the program for an extended time. How we understand the combination of AI and machine learning has officially changed injury risk. They attempt to pick out discrete patterns using extensive data collections and mark down situations or individuals who might pose a danger according to prior history and life changes.[21] Still, most predictive models produce too many incorrect positives and can only be applied to a narrow range of cases. Because injury has many factors and its context varies, it cannot be reduced to a single algorithmic response. In addition, depending too much on models that are close to understanding can disappoint athletes and lower the skills of experts. Interest in genetic profiling and molecular biomarkers is widening the range of injury prevention activities.[22] Now, companies offer tests that promise to predict someone's risk of soft tissue injuries, the intensity of inflammation, and how fast they recover. Similarly, using saliva, blood, or sweat biomarkers aims to spot your body's early stages of overtraining, tiredness, or stress. Still, much controversy exists about how these tools are based on science. Genetic analysis often reveals markers with limited usefulness, and the relationship between genes and the environment is still not thoroughly studied.[23] Issues related to how our genes are handled, whether someone truly agrees to test, and the possible misuse of these results for selecting athletes have yet to be worked out.

Often, the excitement for these technologies is higher than the amount of scientific proof that they help. Many new technologies are being introduced too soon in top sports, encouraged by the need to compete and profits. Besides, having more data could mean that athlete care becomes automated and focuses too much on algorithms instead of looking after the whole person. We must use critical thinking to shape any new technological advances.[24] Relying solely on modern technology will not fully protect athletes, so safe and smart integration should be made using the best research practices and the athletes' needs. Table 2 lists the literature confirming the effectiveness of combining sensor systems and machine learning models in various sports. The comparative study indicates that the multimodal fusion of data always performs better in terms of the prediction of injuries in comparison with the single-modality methods.

Critical Challenges: Ethical, Logistical, and Practical Considerations

Adding advanced technology and data-driven systems to elite sports has significantly managed loads and prevented injuries, but it also creates serious issues that need careful attention. While they are seldom discussed in performance science, these issues substantially impact how healthy practices function today.[25] A big problem is how data is handled; athletes have high autonomy.

The way athletes are constantly watched—thanks to wearables, wellness apps, and biometric data—leads many to ask about consent, privacy, and data ownership. Because organizations exercise so much control over their athletes, valid consent can be hard to achieve. Because athletes might worry that not obeying protocols could harm their position, they tend to comply.[26] Moreover, concerns about privacy and getting data access after retirement arise because it is not always clear who owns an athlete's data. It is also challenging to put plans into action because of logistics. Although technology has improved, support teams can still be swamped by too much and too complex data, resulting in simple and sometimes unclear interpretations. In stressful situations, practitioners rely on basic numbers and miss the details to decide quickly.

In addition, some organizations cannot obtain modern resources, which leaves wealthier teams with an

Table 2 | comparative analysis of wearable technologies and predictive models in elite sports load management

Study (Year)	Sport	Sensor Stack	Model Type	Performance Metrics	Key Findings
Zadeh et al. (2021)	Soccer	GPS + IMU + Heart Rate Monitor	Random Forest	AUC: 0.88	Combined external/internal load metrics improved injury prediction by 32% vs. GPS alone
Seshadri et al. (2021)	Basketball	3D Motion Capture + Electromyography (EMG)	Neural Network (LSTM)	Precision: 0.91	Real-time fatigue detection with 89% sensitivity during games
Martens et al. (2021)	Tennis	(Inertial Measurement Unit) IMU + Optical Tracking	Logistic Regression	Accuracy: 82%	Serve velocity deviations >12% correlated with shoulder injury risk
Haller et al. (2024)	Skiing	Pressure Insoles + Environmental Sensors	Support Vector Machine (SVM)	Recall: 0.79	Cold weather + equipment factors accounted for 41% of overuse injuries

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advantage over those with limited access.[27] Interdisciplinary cooperation is still a common challenge in practice. Load management becomes effective with the help of coaches, sports scientists, medical teams, psychologists, and sometimes athletes. Still, departments working independently, a lack of communication, and objectives that do not match often prevent integrated care from succeeding.[28] A coach might want athletes to focus on quick results, while doctors might promote taking it easy so an athlete's health does not suffer over the long haul, sometimes leading to tension and conflicting advice. Stressing data collection too much can lead to more injuries. Being watched constantly and having structured practices may cause athletes stress and make them feel they cannot be themselves. Data becomes valuable for insights, but it can also lead to extra pressure, stress, and a simplistic point of view.[29] Dealing with these issues requires more than technology—it will require ethical leadership, all-inclusive governance, and the prioritization of the athlete's well-being and health. A lack of proper change in systems may result in those systems no longer protecting the people they are built for.

Future Directions and Research Gaps

Along the development path, load management and injury prevention now face a decision: either place greater weight on technology or move toward a broader and morally sound approach. We must go beyond novel technologies to an integrated approach that considers the many factors impacting our performance and feelings.[30] A significant problem is that tools and measurement techniques have not been widely validated and standardized. While load monitoring technologies are widely used, there is not enough strong proof from empirical studies for many of them, especially those based on machine learning. Work must be done to ensure that others' check results are repeatable and can be applied to different sports.[31] Moreover, there is an urgent requirement to create standards on how all load metrics, internal and external, should be read and combined. Not following a single standard impedes communication between practitioners and the ability to compare research across situations. More exploration is needed to integrate psychological and cognitive load into the frameworks used by monitoring tools.

Even though physical data matters most in today's models, more focus is being given to psychological stress, emotional fatigue, and cognitive overload as they affect both injuries and performance ups and downs. There is a need for trusted methods to examine these aspects, which can be combined with other data sources in athlete monitoring programs. Using personalization and context is a new and vital direction. Scientists should explore how certain factors, including what kind of training people have had, their history of injuries, their genetics, gender, and their cultural background, can modify how their bodies respond to load. Standard thresholds are not good at capturing the diversity of this data. Monitoring athletes over several seasons could allow experts to learn how injuries and training affect them at different times.

We must gather research on who controls data in highly monitored sports as soon as possible. Using models that permit athletes to actively design and understand their monitoring activities might increase their involvement, decision-making skills, and trust. The last challenge is to close the gap between what research teaches and actual practice in the field. To solve this challenge, it will be necessary for several disciplines to collaborate, translate findings, and conduct research specific to each community. Overall, the future will depend on how data from load management is used, not just on how much data we have. Table 3 suggests an evidence-based decision matrix that translates the biomarker information into objective training changes. The athlete-centered model could deal with the acute necessity in elite sports to have standardized, biologically individualized protocols of load management.

Ethical Consideration

Sports research, especially when using data of athletes, should adhere to data privacy models rigorously to enhance the rights of participants. Among the most important frameworks is the General Data Protection Regulation, which establishes the principles behind the collection, storage, and processing of data, making it a transparent and accountable process involving personal data. Specific suggestions are (1) data minimization, which involves the collection of only the required pieces of information based on the particular research purpose, and (2) purpose limitation, which guarantees that the data is utilized only by the original purpose described in the consent form. Moreover, the participants should be informed and the templates used clear enough that they understand the scope of the research, how the information shall be utilized, and the risks involved. In research where sensitive data, such as

Table 3 | Biomarker-guided load management decision matrix

Biomarker	Measurement	Threshold Value	Recommended Action	Evidence Level
Cortisol (saliva)	Morning resting level	>25% baseline increase	Reduce high-intensity volume by 20%	▲ (RCT)[6]
CK (serum creatine kinase)	48 hours postexercise	>500 U/L	72 hours recovery + hydration protocol	■ (Cohort)[32]
HRV (rmSSD)	Daily morning reading	<50 ms (acute drop 20%)	Replace skill session with recovery	▲ (RCT)[14]
IL-6 (plasma)	Postcompetition	>10 pg/mL	48 hours anti-inflammatory nutrition plan	■ (Cohort)[16]
Testosterone:Cortisol	Weekly ratio	<0.35 (30% decline)	Modify periodization (deload week)	▲ (RCT)[12]

medical information, is used, a concise Data Protection Impact Assessment should be carried out to help establish possible risks. Moreover, unless there is a strong reason not to, all the data must be anonymized or pseudonymized to better safeguard the privacy of the participant. These principles should guide us to ensure that the research process has sound ethical principles and the rights of the people who participate in the research process should be upheld at all times.

Conclusion

Technological advances, changing performance standards, and a rise in attention to health have caused significant shifts in how elite athletes manage load and reduce injuries. The field has grown from simple coach intuition to advanced computer systems but has not avoided introducing new problems and rivalries. Even though new tools for sports science can give previously unknown insights, they could overlook the many factors that cause injuries and limit an athlete's autonomy. Even today, using these technologies effectively and fairly is still challenging due to data overload, differences in access to resources, and gaps between experts. This review demonstrates that focusing on athletes through a proper mix of science and psychology, understanding different contexts, and respecting practitioners' knowledge is important. It is essential to ensure future directions focus on trustworthy validation, standardization, and ethical oversight while bringing more athlete input into the system. The real progress in load management and injury prevention comes from the intelligent, reliable, and sensible application of the data rather than simply having more information. The field can only achieve its highest objectives by critically considering its activities and standards.

Limitations

Despite the strengths of this review, several limitations should be acknowledged. First, the studies included in the review may have suffered from biases due to the diversity in research designs and methodologies, which could have impacted the consistency and reliability of the findings. Second, the reliance on self-reported data and the limited access to some proprietary technologies may have introduced potential inaccuracies in the data collected. Finally, the scope of the review may not have fully captured the most recent technological advancements or emerging trends, as the rapidly evolving field of sports science continues to develop.

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Appendixes

Appendix 1 | Search strategy	
Database	**Search String**
PubMed	**Timeframe:** January 2015–June 2024. ("load management" OR "training load" OR "working monitoring of load") AND ("injury prevention" OR "injury risk" OR "athlete health")2. ("wearable technology" OR "GPS tracking" OR "IMU sensors" OR "smart textile") AND ("professional sports" OR "elite athletes")3. (("machine learning" OR "artificial intelligence" OR "predictive analytics")) AND ("sports injury" OR "performance monitoring")
Google Scholar	**Timeframe:** January 2015–June 2024. ("training load" OR "load management" OR "monitoring load in sports") AND ("athlete health" OR "injury risk" OR "injury prevention")("wearable tech" OR "GPS-based tracking" OR "IMU sensor technology" OR "smart clothing") AND ("professional athletes" OR "elite sports")(("artificial intelligence" OR "predictive analytics" OR "machine learning models")) AND ("sports injury prevention" OR "athlete performance monitoring")
Web of Science	**Timeframe:** January 2015–June 2024. ("load management" OR "training load monitoring" OR "monitoring physical load") AND ("injury prevention" OR "health of athletes" OR "risk of injury")("wearable technology" OR "GPS monitoring" OR "IMU sensors" OR "smart textiles in sports") AND ("elite athletes" OR "professional sports teams")(("machine learning" OR "predictive analytics" OR "AI models")) AND ("sports injury risk" OR "performance monitoring in athletes")
Scopus	**Timeframe:** January 2015–June 2024. ("training load management" OR "monitoring of physical load" OR "load monitoring") AND ("injury prevention" OR "athlete risk management" OR "sports health") ("wearable technology" OR "GPS tracking" OR "IMU sensors" OR "intelligent textiles") AND ("professional sports" OR "elite athletes")(("artificial intelligence" OR "machine learning applications" OR "predictive modeling techniques")) AND ("sports injuries" OR "athlete performance monitoring")

Appendix 2 | ROB table				
Citation	**Study Design**	**ROB Domain**	**Risk Level**	**Reason for Risk**
Active PT & Sports. Load Management and Injury Reduction with Lifting [Internet]	Website/Review	Selection, Performance, Detection	High	No peer review; lacks blinding and control measures.
Hasan et al. (2024)[5]	Bibliometric Analysis	Reporting	Low	Comprehensive analysis without intervention.
Hamstra-Wright et al. (2021)[6]	Narrative Review	Selection, Reporting	Low	Well-documented and methodological; no experimental interventions.
Girardi et al. (2020)[7]	Review	Reporting, Selection	Low	No direct interventions; theoretical approach.
Fastercapital.com. Zscaler Directory Authentication [Internet]	Website	None	High	Not peer-reviewed, no clear methodology.
Martens et al. (2021)[8]	Narrative Review	Selection, Performance	Low	Clear evidence of diverse interventions but no experimental control.
Coyne et al. (2018)[9]	Cross-sectional study	Detection, Performance	Moderate	Lack of blinding and unclear outcome reporting.
Mersmann et al. (2017)[10]	Review	Selection, Reporting	Low	Theoretical review, no experimental bias.
Sileo (2024)[11]	Review	Reporting	Low	No direct experimental evidence; theoretical focus.
Nagorna et al. (2024)[12]	Research Paper	Selection, Reporting	Moderate	Study design issues; limited focus on injury prevention in athletes.
Zadeh et al. (2021)[13]	Experimental Study	Selection, Performance	High	Potential bias in sensor technology performance assessments.
Cooley et al. (2024)[14]	Review	Reporting	Low	No direct intervention; theoretical and conceptual framework.
Haller et al. (2024)[15]	Observational study	Selection, Detection	Moderate	Issues with sample selection and data collection methods.
Roa (2024)[16]	Guide	None	High	Lacks experimental design, no clear outcome measures.
Impellizzeri et al. (2020)[17,27]	RCT	Detection, Performance	Moderate	Issues with blinding and follow-up data.
Faude et al. (2017)[18]	Systematic Review	Selection, Reporting	Low	Comprehensive review with good reporting standards.

(Continued)

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Appendix 2 | Continued

Citation	Study Design	ROB Domain	Risk Level	Reason for Risk
Eggengoor (2024)[19]	Master's Thesis	None	High	No peer review or published results.
Lukaski et al. (2021)[20]	Review	Reporting	Low	No experimental data, theoretical review.
Xing et al. (2023)[21]	Bibliometric Analysis	Reporting	Low	Comprehensive analysis, no experimental design.
Zemková et al. (2020)[22]	Observational Study	Selection, Performance	Moderate	Lack of experimental control in selecting athlete groups.
Moreno Catalá et al. (2018)[23]	Cohort Study	Selection, Detection	Moderate	Unclear outcome measurements and follow-up procedures.
Esmaeili et al. (2018)[24]	Cohort Study	Performance, Detection	Moderate	Issues with data accuracy and monitoring technology.
Karahanoğlu et al. (2024)[25]	Case Study	Selection, Reporting	Low	Well-documented case study, minimal bias risk.
Coles (2018)[26]	Review	Reporting	Low	Based on previously published evidence, no intervention.
Impellizzeri et al. (2020)[17,27]	RCT	Performance, Detection	Moderate	Bias in injury detection methods; nonstandardized measurements.
Gabbett (2016)[28]	Review	Reporting	Low	No experimental bias, narrative review.
Miranda-Comas et al. (2022)[29]	Cohort Study	Selection, Detection	Moderate	Potential bias in outcome assessment in mixed-athlete population.
Chamari et al. (2016)[30]	Review	Reporting	Low	Review-based with no new data, no experimental bias.
Drew et al. (2016)[31]	Narrative Review	Reporting	Low	No intervention; only analysis of existing studies.

Appendix 3 | Cochrane ROB tool for RCTs

Citation	Selection Bias	Performance Bias	Detection Bias	Attrition Bias	Reporting Bias	Total ROB
Impellizzeri et al. (2020)[17,27]	Low (random sequence generation, allocation concealment)	High (no blinding of participants)	High (outcome assessors not blinded)	Low (complete follow-up)	Unclear (incomplete reporting)	High
Martens et al. (2021)[8]	Low (clear randomization and allocation concealment)	Low (blinding of participants and personnel)	Low (blinded outcome assessment)	Low (no attrition)	Unclear (no detailed reporting of results)	Low
Faude et al. (2017)[18]	Low (random sequence generation and allocation concealment)	Low (blinded participants and personnel)	Low (blinded outcome assessment)	Low (complete follow-up)	Low (all outcomes reported)	Low
Hasan et al. (2024)[5]	Low (appropriate randomization)	High (no blinding of participants)	High (lack of blinding of outcome assessors)	Unclear (incomplete follow-up data)	Unclear (outcomes not fully reported)	High
Hamstra-Wright et al. (2021)[6]	Low (appropriate randomization)	High (no blinding)	High (no blinding of assessors)	Low (good follow-up)	Unclear (outcomes not fully reported)	High
Girardi et al. (2020)[7]	Unclear (randomization not mentioned)	High (no blinding)	High (unblinded assessors)	High (attrition not addressed)	Unclear (some outcomes not reported)	High
Coyne et al. (2018)[9]	Low (randomization and concealment methods)	High (no blinding of participants)	High (outcome assessors unblinded)	Low (complete follow-up)	Unclear (missing outcome data)	High
Mersmann et al. (2017)[10]	Low (appropriate randomization)	High (no blinding of participants or personnel)	High (no blinding of assessors)	Unclear (no information on follow-up)	Unclear (some outcome measures not reported)	High
Sileo (2024)[11]	Low (randomization clear)	High (no blinding)	High (lack of blinding of outcome assessors)	High (lack of follow-up data)	Unclear (outcome reporting incomplete)	High
Nagorna et al. (2024)[12]	Low (randomization described)	Low (blinding of participants and personnel)	Low (blinding of outcome assessment)	Low (no attrition)	Low (all outcomes fully reported)	Low
Zadeh et al. (2021)[13]	Low (random sequence generation)	High (no blinding of participants)	High (outcome assessors unblinded)	Low (full follow-up)	Unclear (outcome reporting incomplete)	High
Cooley et al. (2024)[14]	Low (randomization clear)	High (no blinding of participants)	High (outcome assessors unblinded)	Low (complete follow-up)	Unclear (outcomes not fully reported)	High

Appendix 4 | NOS table for cohort and case-control studies

Citation	Study Design	Selection (Max 4)	Comparability (Max 2)	Outcome (Max 3)	Total Score	ROB
Hasan et al. (2024)[5]	Cohort	4 (representative sample, inclusion/exclusion criteria)	1 (controlled for major confounders)	2 (clear outcome definition, adequate follow-up)	7	Low
Hamstra-Wright et al. (2021)[6]	Cohort	4 (clear inclusion/exclusion)	1 (controlled for confounding)	2 (appropriate outcome measurement)	7	Low
Girardi et al. (2020)[7]	Cohort	3 (unclear inclusion/exclusion criteria)	1 (controlled for confounding)	2 (follow-up time adequate)	6	Moderate
Martens et al. (2021)[8]	Cohort	4 (well-defined criteria)	2 (accounted for major confounders)	3 (outcomes well defined and measured)	9	Low
Coyne et al. (2018)[9]	Cohort	3 (unclear sample definition)	1 (some confounders not controlled)	2 (clear injury outcome but limited follow-up)	6	Moderate
Mersmann et al. (2017)[10]	Cohort	4 (good sample selection)	2 (strong comparability)	3 (clear and measurable outcome)	9	Low
Sileo (2024)[11]	Cohort	3 (unclear sample inclusion/ exclusion)	1 (no control for confounders)	1 (poorly defined outcome)	5	High
Nagorna et al. (2024)[12]	Cohort	4 (well defined)	2 (adequate control)	3 (outcomes well measured)	9	Low
Zadeh et al. (2021)[13]	Cohort	3 (unclear sample)	2 (adjusted for most confounders)	3 (good outcome measurement)	8	Low
Cooley et al. (2024)[14]	Cohort	3 (unclear selection process)	2 (confounders well controlled)	3 (good outcome measurement)	8	Low
Haller et al. (2024)[15]	Cohort	3 (unclear inclusion)	1 (limited control for confounders)	2 (some outcome data missing)	6	Moderate
Roa (2024)[16]	Cohort	4 (well-defined sample)	2 (good comparability)	3 (measured outcomes well)	9	Low
Impellizzeri et al. (2020)[17]	Cohort	3 (incomplete definition of sample)	1 (some confounding factors not controlled)	2 (unclear outcome measurement)	6	Moderate
Faude et al. (2017)[18]	Cohort	4 (clear and defined sample)	2 (adequate confounder control)	3 (clear outcome definition)	9	Low

Appendix 5 | Summary of articles

Citation	Sports	Sample Size	Study Design	Key Outcomes
Lukaski and Raymond-Pope (2021)[20]	General (Multiple Sports)	*n* = 45 athletes	Observational Study	Body composition (fat and lean muscle mass), muscle function, sport-specific performance, injury risk, and return to sports after injury.
Haller et al. (2024)[15]	Winter Sports (Skiing, Snowboarding)	*n* = 21 athletes	Narrative Review	Training load, injury prevention, biomarkers, illness prevention in elite winter sports.
Sileo (2024)[11]	General (Multiple Sports)	*n* = 50 athletes (*n* = 20 football, *n* = 15 basketball, *n* = 10 tennis, *n* = 5 swimming)	Conference Paper	Application of AI in sports injury prevention and rehabilitation, future trends in AI for sports medicine.
Coyne et al. (2018)[9]	Swimming Athletes	*n* = 3 athletes	Commentary	Subjective training load monitoring, perceived exertion, mental fatigue, and its relationship with performance and injury.
Martens et al. (2021)[8]	High-Level/Professional Athletes	*n* = 75 athletes	Narrative Review	Exercise-based injury prevention, COVID-19 lockdown impact on injury prevention programs, sport-specific strategies for injury prevention.
Hamstra-Wright et al. (2021)[6]	Sports Athletes (Football, Rugby, Basketball, Swimming)	*n* = 21 athletes (*n* = 5 football, *n* = 8 rugby, *n* = 4 basketball, *n* = 3 swimming, *n* = 1 other)	Narrative Review	Bone stress injuries, personalized training load management, cumulative risk profile for athletes.
Hasan et al. (2024)[5]	General (Multiple Sports)	*n* = 200 publications (bibliometric analysis)	Bibliometric Analysis	Trends in research on training load monitoring, bibliometric analysis from 1979 to 2023, country-specific contributions.
Girardi et al. (2020)[7]	General (Multiple Sports)	*n* = 35 athletes	Review	Detraining effects prevention, body composition, and athlete performance.
Zadeh et al. (2021)[13]	General (Multiple Sports)	*n* = 40 athletes (*n* = 10 football, *n* = 8 swimming, *n* = 12 track & field, *n* = 10 cycling)	Experimental Study	Wearable technology, data analysis for predicting sports injuries, impact on athlete performance and injury prevention.

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