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Review Article

Big Data in Sports Medicine and Exercise Science: Integrating Theory and Practice for Future Innovations

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Abstract

Background: Big data has been successfully applied in medicine, offering remarkable advancements in patient care and health management. The rise of big data in sports medicine and exercise science is a pivotal development, offering new perspectives regards athlete performance, preventing injuries, and managing non-communicable diseases (NCDs).

Objectives: The objectives of this study were: (i) to present the current state of big data in sports medicine, including its applications and advancements in wearables, genomics, and metabolomics, and (ii) to outline the future prospects of big data in sports medicine and exercise science, emphasizing a call to action for ongoing research and interdisciplinary collaboration.

Methods: This narrative review examined the existing literature on big data applications in sports medicine, primarily targeting athlete health management and secondarily addressing the management of NCDs. The focus was on wearables, genomics, and metabolomics. A comprehensive search of academic databases identified pertinent articles, with an emphasis on their relevance to athlete performance enhancement and applicability in managing NCDs.

Results: The study's findings emphasize the profound benefits of big data across three key areas in sports medicine and exercise science: wearables, genomics, and metabolomics. For athletes, big data in wearables has advanced real-time physiological monitoring and injury prediction, leading to customized training and rehabilitation programs that enhance performance while minimizing injury risks. In genomics, the integration of big data has unveiled genetic factors affecting athletic performance and injury vulnerability, facilitating tailored athlete care and training optimization. Similarly, in metabolomics, big data's application has deepened the understanding of metabolic reactions to exercise, guiding personalized nutrition and recovery plans crucial for optimal athletic performance. Additionally, these advancements extend to people living with NCDs, where big data contributes to improved health management through refined monitoring and personalized intervention strategies.

Conclusion: The incorporation of big data into sports medicine and exercise science significantly advanced athlete care and health management. Wearable technologies transformed the landscape of real-time physiological monitoring, enabling the development of personalized training programs that improved performance and reduced injury risks. Genomics, supported by big data, provided valuable insights into genetic factors affecting athletic performance, guiding more precise and individualized approaches in sports medicine. In metabolomics, the application of big data enhanced our understanding of metabolic responses to exercise, contributing to more effective nutrition and recovery strategies. Additionally, these advancements in big data also showed promise for managing NCDs, offering potential for more personalized and effective health interventions. This convergence of technology and science has elevated athletic performance and contributed to broader health and fitness strategies, marking a significant step forward in personalized and data-driven healthcare.

Keywords: *Athletic Performance, Biomechanics, Data Analytics, Deep Learning, Epidemiology, Injury prediction, Machine Learning, No-contact injuries, Omics, Personalized Medicine, Proactive health, Proteomics, Rehabilitation, Sensors, training load, transcriptomics.*

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1. Introduction

The integration of big data into healthcare has led to a new era of medical research and practice (1). In modern medicine, big data has become essential due to its large volume, quick processing speed, and diverse range of information. Its emergence comes from the need to handle an increasing amount of patient' data and the complex dynamics of disease patterns (1, 2). Medical practitioners and researchers can now navigate through immense datasets, identifying patterns and correlations that were previously unattainable (3). This development has enhanced the efficiency of patient care and fundamentally transformed our approach to illness prevention, diagnosis, and treatment (1-3). Big data facilitates personalized medicine by examining patient records and genetic data (4), allowing for customized therapies based on individual genetic profiles (4). Furthermore, it serves as a vital component in the field of epidemiology and public health, aiding in the timely identification of disease outbreaks and the monitoring of health patterns (5). The utilization of big data has resulted in more efficient methods for handling chronic illnesses, maximizing healthcare assets, and developing public health regulations (2). Additionally, the incorporation of machine learning and deep learning into big data analytics has further enhanced the capacity to extract meaningful insights from complex datasets, enabling more nuanced decision-making in medical care (6).

While big data has long been utilized in general care, its application in sports medicine and exercise science is still in its initial stages. The field of sports medicine and exercise science, offers big opportunities for the utilization of big data applications. Nevertheless, the present utilization of big data in this domain is somewhat restricted, mostly focused on injury prognosis and performance analysis (7). The potential of big data combined with machine learning and deep learning technologies to change sectors such as athlete rehabilitation, recovery processes, and management of physical activity's related non-communicable diseases (NCDs) is promising. The early stage of implementing big data in sports medicine reveals a discrepancy between what is conceivable and what is currently being done, indicating significant potential for expansion and investigation.

Based on the underutilization of big data, machine learning, and deep learning in sports medicine, and the need for more comprehensive applications in areas like rehabilitation and NCD management, the objectives of this article are two-fold: (i) to present the current state of big data in sports medicine and exercise science, highlighting its applications and advancements particularly in wearables, genomics, and metabolomics, and (ii) to outline the future prospects of big data in sports medicine and exercise science, specifically in managing and preventing NCDs, optimizing rehabilitation processes, and enhancing athletic performance.

2. Big Data in General Medicine: Foundations and Progress

In recent years, the application of big data in medicine has brought about significant advancements in healthcare, particularly in the areas of health outcomes, genetics, management of NCDs, rare diseases, and the development of personalized medicine (1, 4).

For instance, the use of wearable technology has become a vital tool in managing chronic conditions such as asthma and blood pressure (8, 9). These devices collect and send data to cloud-based systems, allowing healthcare providers to remotely monitor patients' health (8, 9). This advancement empowers patients by giving them more control over their health and reduces unnecessary hospital visits, thereby improving the efficiency of healthcare delivery. Big data has played a crucial role in addressing public health crises like the opioid epidemic in the US (8, 10). Through the analysis of insurance and pharmacy data, analysts have been able to identify risk factors for opioid abuse (8). This proactive approach has provided new strategies for preventing drug abuse, demonstrating big data's potential in tackling large-scale public health issues (8).

The strategic planning of healthcare resources has also been enhanced through big data. For instance, the integration of public health data with tools like Google Maps has enabled institutions to identify regions with high incidences of chronic diseases (8). This approach aids in allocating healthcare resources more effectively, ensuring that areas with greater healthcare needs receive adequate support.

In the field of cancer research and treatment, big data has also been instrumental. The Cancer Moonshot program is a notable example, where big data on treatment plans and recovery rates have been used to identify the most effective cancer treatments (8, 11). This approach has enabled medical researchers to discover trends and treatments that lead to better patient outcomes, highlighting the pivotal role of big data in advancing cancer research.

Predictive analytics, another application of big data, has significantly improved patient care. By analyzing electronic health records (EHRs) of millions of patients, healthcare providers can make more informed decisions, especially for patients with complex medical histories (12). This predictive ability is crucial in early identification and intervention for diseases like diabetes. Big data has also enabled patients to access their medical records easily, empowering them to participate actively in their health management. Additionally, big data supports healthcare providers with comprehensive and up-to-date information on patients' health statuses, leading to faster and more accurate treatment assessments (12).

Healthcare professionals can enhance their understanding of a patient's health by utilizing big data approaches to standardize patient datasets, incorporating various data sources (such as smart devices and patient questionnaires) (8). This integrated approach results in treatment regimens that are tailored to individual needs and are more efficient in achieving desired outcomes (8). Furthermore, the utilization of big data has extended the scope of healthcare services by enhancing telehealth systems (8). The utilization of smart devices has also facilitated the provision of medical care to patients residing in remote places, hence mitigating the disparity in healthcare accessibility. The implementation of automated patient data analysis and treatment recommendations has enhanced the efficiency of the healthcare process, hence increasing the accessibility of medical care to a wider demographic (8).

3. Machine Learning and Deep Learning in Medicine: Enhancing Big Data

Combining the techniques of machine learning and deep learning with big data has greatly enhanced the capacities of medical analysis and decision-making. Machine learning, a subfield of artificial intelligence, involves the use of algorithms that acquire knowledge and generate predictions when analyzing data (13). Deep learning is an advanced type of machine learning that use neural networks consisting of numerous layers to examine complex patterns in large datasets (13). These technologies in the field of medicine have facilitated the development of more advanced and nuanced analyses of medical data (13). Machine learning algorithms have been employed to examine medical pictures, such as MRIs and X-rays, effectively detecting minute patterns that may go unnoticed by human observers (14). It has enhanced the precision of diagnosing illnesses such as cancer and neurological or osteoarticular conditions, for instance (15, 16).

The field of genetics and personalized medicine has shown remarkable potential with the application of deep learning techniques (4). Through the examination of large genetic databases, deep learning algorithms have the ability to forecast an individual's predisposition to specific illnesses, thus enabling the implementation of preventative healthcare approaches. This method is especially advantageous in the management of chronic illnesses such as diabetes, as it allows for the creation of individualized treatment strategies based on a patient's genetic makeup (17). By examining trends in patient data through machine learning and deep learning, algorithms have the ability to forecast the probability of different outcomes, assisting doctors in making well-informed decisions regarding patient care. This encompasses the ability to anticipate the probability of hospital readmission for patients who have previously been admitted, as well as the probability of encountering difficulties during surgical procedures (18). Although machine learning and deep learning have great potential, their implementation in the field of medicine encounters various obstacles. An essential concern is the data quality issues. The necessity for high-quality data is fundamental for the effective training of these algorithms. Key issues in data quality include accuracy, completeness, and consistency, which are essential for reliable algorithmic predictions and analyses (18). Additionally, the volume of data required to train complex models, especially in deep learning, is substantial. Ensuring that the data is not only large in quantity but also diverse and representative is critical to avoid biases and to improve the generalizability of the models (18).

4. Current State of Big Data in Sports Medicine

The use of big data into sports medicine represents a significant transformation in the discipline, with a growing emphasis on optimizing athletic performance and mitigating the occurrence of injuries (19). This evolution also applies to areas beyond sports, providing valuable knowledge on the management and prevention of NCDs. The utilization of big data in this field exploits advanced technologies and analytical algorithms, resulting in more individualized and efficient approaches in athlete healthcare and overall fitness (9, 19).

4.1. Use of big data in Wearables technology

Wearable technology, which includes a variety of devices such as WHOOP®, the Apple® Watch among others, plays a critical role in modern health monitoring (20, 21). These devices, chosen here as examples due to their widespread use, are employed for real-time monitoring of various physiological parameters.

WHOOP, for instance, uses algorithms trained on extensive data sets to analyze sleep patterns, heart rate variability, and recovery levels, linking these factors directly to athletic performance (20, 21). The Apple Watch, in particular, has capabilities that extend beyond fitness tracking, making it a valuable tool in broader healthcare contexts, especially for individuals living with NCDs (22). The Apple Watch is renowned for its comprehensive health tracking features. Among its many functions, a notable one is its ability to monitor heart rhythms (23, 24). Studies have demonstrated the Apple Watch's capabilities in detecting atrial fibrillation (AFib), a common cause of stroke, through its irregular rhythm notification and electrocardiogram (ECG) app (23, 24). This feature holds significant potential for preventing strokes, especially in individuals with NCDs. The expanded use of wearable technology in sports medicine includes the monitoring of several vital parameters. These wearables can track blood oxygen saturation (SpO2), skin temperature, breathing rate, sleep patterns, and daily steps (25). This comprehensive data collection is crucial in providing practical applications for athletes. For example, monitoring SpO2 and skin temperature can give insights into an athlete's recovery status or alert to potential health issues (23). Tracking sleep and steps helps in understanding an athlete's overall well-being and readiness for training and competition. Thus, wearable technology can aid in optimizing training schedules, preventing overtraining, and ensuring effective recovery, thereby enhancing athletic performance and health management.

4.2. Use of big data in Genomics

In addition to wearable technology, the field of genomics in sports medicine is emerging as a significant area of research. Genomics in sports medicine, focuses on identifying genetic factors that influence physical performance and injury risks. Sports genetics and genomics have significantly advanced our understanding of physical performance outcomes and injury risks in athletes. A study by Ahmetov and Fedotovskaya (26) have highlighted the influence of 155 genetic biomarkers on elite athlete status, encompassing a range of athletic traits. These markers, found in almost all chromosomes and even mitochondrial DNA, are associated with endurance (93 markers) and power/strength (62 markers) (26). Among these markers, some genes stand out for their specific associations with athletic abilities and injury susceptibility (27). For instance, the VDR gene is linked to physical strength, and the BDKRB2 gene to muscle strength and efficiency (26) while ACE polymorphism strongly characterizes athletes compared to the general population (28). The DRD2 gene affects physical behavior and motivation, while ACTN3 is associated with muscle contraction, speed, and power (26). It is also suggested that mental profiles of endurance or power sport athletes are associated with the genetic polymorphism to physical activity (29). Genes like ADRA2B and ATP1A2 influence metabolism and aerobic capacity, respectively. In terms of injury risk, genes such as MMP-3, BMP-4, and others in the RANK/RANKL/OPG pathway have been identified as potential injury' predictors (25).

Indeed, these genetic insights may have many practical implications. For example, polymorphisms in these genes may contribute to the etiopathogenesis of common sports-related injuries like Achilles tendinopathy (27). Similarly, genomics studies have identified SNPs in genes like ZNF804A and GLCCI1, which are implicated in the development of shoulder pathologies (30). Furthermore, polygenic/genotype-based scores, as explored by Sillanpää et al. (31), Ben-Zaken et al. (32), and Lee et al. (33), are now being used for profiling athletes. These scores predict the effects of training programs and strategies, offering a more personalized approach to athlete training and performance enhancement.

4.3. Use of big data in metabolomics

Metabolomics, a facet of 'omics' science that extensively measures small metabolites in biological samples, has become increasingly prominent in sports medicine (15, 34). Termed "sportomics," this approach is crucial in studying exercise physiology and metabolism. The integration of big data in metabolomics is significantly enhancing our comprehension of athletes' physiological responses to exercise (34).

One of the remarkable advancements in sportomics is its application across various sports disciplines (34). For instance, studies on runners, cyclists, soccer players, basketball players, and rugby players have illuminated the profound metabolic shifts induced by different types of physical activities (34). These studies, employing a range of metabolomics technologies, have been critical in identifying biomarkers linked to exercise and recovery. For example, a study by (35) in soccer players identified metabolites related to fatigue, providing insights into athlete performance and recovery.

Technological advancements in metabolomics, particularly in mass spectrometry techniques like CE-MS, LC-MS, GC-MS, and NMR spectroscopy, have propelled the field even further (34). Each method has its unique strengths, influencing their application in sports medicine based on specific research needs and sample types (34). For instance, NMR spectroscopy, with its precise metabolite identification capabilities, and MS-based methods, with their broad metabolite detection range, have each contributed to a deeper understanding of metabolic changes in athletes (34).

The focus of metabolomics research in sports has been on understanding how exercise influences metabolite levels and pathways. Notably, the studies have concentrated on exercise nutrition metabolism and sport-specific metabolism. For example, (36) used a multiplatform metabolic phenotyping approach to study metabolic profiles in rugby players. Their findings highlighted significant differences in metabolite levels between athletes and controls, providing a clear understanding into the metabolic impacts of intense physical activity (32, 37) have shown that different metabolic profiles are characterizing backcourt and frontcourt elite basketball players. Indeed, they showed that aerobic metabolic changes are more present in the backcourt players, while frontcourt players show greater changes in anaerobic metabolic pathways due to more powerful movements (37).

A key aspect of metabolomics in sports medicine is the growing trend towards non-invasive sample collection methods such as saliva and urine. This approach aligns with ethical research practices and is more convenient for monitoring athletes' metabolic responses over time. For instance, the study by (38) on elite soccer players employed saliva samples to analyze the impact of physical exertion, demonstrating the practicality and effectiveness of non-invasive metabolomics in sports settings.

Despite these advancements, challenges remain in the field. Many studies suffer from statistical inconsistency and small sample sizes, limiting the generalizability of findings. Additionally, the lack of standardized protocols for metabolite quantification across different labs and studies has been a significant obstacle.

5. Future prospects of Big Data in Sports Medicine: a call for action

In this examination of big data's role in sports medicine and exercise science, we recognize the speculative yet growing potential of this technology. The application of big data is evolving, impacting various facets of these fields. This section presents as a call to action for researchers and scientists exploring the expansive potential of big data in sports medicine and exercise science. We urge the scientific community to deeper explore and build upon the suggested ideas, utilizing big data to revolutionize sports medicine and exercise science.

5.1. Big data and wearable technologies

Driven by the rapid advancements in engineering and biotechnology, the future of wearable technology in sports medicine, is set to cross new frontiers (9). These rapidly evolving tools are offering sophisticated means for monitoring and enhancing athlete performance and health management (9). This progression is about incremental improvements and a transformative leap in how we understand and manage both athletic performance and chronic conditions like type 2 diabetes mellitus (T2DM) and hypertension.

One of the most promising areas of development is in non-invasive monitoring of blood sugar levels. Current research is moving towards the use of advanced sensors capable of analyzing sweat composition to provide real-time glucose monitoring (39). This technology, once completely refined, could be a game-changer for athletes and for individuals at risk of developing T2DM. It would allow for continuous monitoring without the need for invasive blood tests, enabling immediate adjustments in diet and exercise regimes. Studies like those by (40) in "Lab on a Chip" have already shown progress in sweat analysis for non-invasive glucose monitoring, indicating the potential of this technology in sports medicine and broader healthcare contexts. Similarly, the development of non-invasive methods for monitoring hormones like cortisol, testosterone, and melatonin directly through wearables could revolutionize athletes’ life and training management. Indeed, such technology would enable the tracking of stress, recovery, and sleep quality, key factors in athletic performance and overall health.

In addition to glucose monitoring, the development of wearable technology capable of non-invasively measuring blood pressure could significantly benefit athletes and individuals with hypertension. These wearables could provide continuous blood pressure monitoring, a critical factor for those with cardiovascular. This could be achieved through innovative approaches such as using optical sensors or other non-invasive methods to measure blood pressure changes. For instance, the work by (41) has explored the use of photoplethysmography, a non-invasive optical method, for monitoring blood pressure, suggesting a pathway for future wearable technology developments. Similarly, (42) showed big potential in concluding that wearable-based pulse arrival time (PAT) contains complementary information about the vascular system to the ambulatory blood pressure, which may be useful for designing effective antihypertensive treatments.

Furthermore, fatigue management in athletes could see remarkable improvements with the advent of more advanced wearables. Technologies that integrate EMG (electromyography) sensors to assess muscle activity and fatigue could provide a better understanding of an optimal training and recovery balance (43). Such developments would enable a more personalized approach to training, reducing the risk of overtraining and injury. Research in this area demonstrates the potential of EMG in understanding muscle fatigue and can inform the design of future wearables (44). The future of wearable technology in sports medicine also holds vast potential in the development of sport-specific algorithms (9, 45). This advancement is particularly relevant in disciplines such as football and basketball, where non-contact injuries are a significant concern (46). These algorithms, tailored to the unique demands and movement patterns of each sport, could be revolutionary in injury prevention.

Incorporating big data analytics into wearables allows for the analysis of large datasets on athlete movements and injury instances. By examining patterns and anomalies in these datasets, algorithms could identify subtle changes in an athlete's movement or gait that may signal an increased risk of injury. This ability could be particularly advantageous in endurance sports like long-distance running, where consistent gait patterns are critical, and deviations can indicate potential issues. In endurance running, where repetitive motion is common, this kind of monitoring can be crucial for early injury detection and prevention. The device could then send an immediate alert to both the athlete and the coach. This real-time warning system would allow for prompt intervention perhaps a change in training intensity or immediate medical assessment potentially averting an injury. Research in this area is emerging. For example, studies like those by (47) have explored biomechanical factors associated with non-contact ACL injuries, laying the foundation for predictive algorithms in wearables. These developments highlight the potential of wearables not just as passive data collectors but as active ''actors'' in injury prevention strategies.

5.2. *The Convergence of Genomics and Big Data in Sports Medicine*

In this section, we look at a group of genes that have gathered significant interest in sports medicine due to their roles in health and athletic performance. The genes previously discussed in the section on the use of big data in genomics have demonstrated their significance in areas such as susceptibility to injuries, athletic performance, and metabolic health. However, it is the integration of big data analytics that has truly unlocked the potential of these genomic findings. Through the application of big data, researchers have been able to analyze vast genomic datasets, identify patterns and correlations, and thus, better understand the complex interplay of these genes in athletic contexts.

Our objective is to reveal novel visions and practical uses in sports medicine and exercise science by employing large datasets and advanced data analysis techniques. Big data is crucial in this endeavor, as it allows for the handling and interpretation of the immense and complex genomic information. Big data have the potential to empower a more personalized approach in sports medicine by analyzing genetic variations and their associations with physical traits and health outcomes.

Indeed, the genetic makeup of athletes may play a crucial role in determining their susceptibility to injuries and their physical capabilities (48). One key gene that has been the subject of research is the COL1A1 gene. This gene is essential in the synthesis of type I collagen, a major component of the human body's connective tissues, including tendons and ligaments. Variations in this gene, when analyzed through big data techniques, can reveal insights into an individual's risk of musculoskeletal injuries.

Posthumus et al. (49) highlighted the significance of the COL5A1 gene. The study investigated the relationship between the COL5A1 gene variant and the risk of anterior cruciate ligament (ACL) ruptures, particularly in female athletes, finding a significant association. This association was made clearer through the analysis of large-scale genomic data, illustrating how big data can elucidate the genetic factors underlying specific sports-related injuries. Another study by (50) examined the role of COL1A1 gene polymorphisms as markers of injury risk, contributing to the understanding of how genetic predispositions can be linked to the likelihood of sports injuries. Again, big data analytics played a critical role in these discoveries, allowing for the examination of genetic variations across large athlete populations.

The ACTN3 gene, encoding the alpha-actinin-3 protein found in fast-twitch muscle fibers, plays a crucial role in sports genomics, particularly in influencing athletic performance in power and sprint activities. The presence or absence of this protein, as determined by the R577X variant of the ACTN3 gene, is associated with an individual's predisposition to either endurance or power sports, respectively (51). This association has been demonstrated in the study of (51), where certain ACTN3 genotypes were found to be overrepresented in elite power athletes compared to the general population. Additionally, the comprehensive review by (52) emphasized the gene's impact on athletic performance. These findings, significantly derived and validated through big data analysis, are pivotal in sports medicine for developing personalized training and injury prevention strategies based on an athlete's ACTN3 genotype, underscoring the integral role of genetics in athletic performance (52, 53).

Another significant gene in sports genomics is the TCF7L2 gene, primarily associated with T2DM risk (54). This gene's role in sports medicine is interesting, particularly in the context of athlete health and performance. TCF7L2 influences insulin secretion and glucose metabolism, factors crucial for energy metabolism in athletes. Studies utilizing big data analytics, such as those by (54), have identified the TCF7L2 gene as a significant contributor to T2DM risk, promoting the body's ability to manage glucose effectively. Moreover, research by (55) further described the gene's impact on insulin production and glucose control. These studies underscore the importance of big data in revealing how variations in this gene can critically affect an athlete's metabolism and guide tailored nutritional and training programs, especially for athletes at risk of or managing their T2DM condition. This approach would enhance both their performance and overall health.

The KCNJ11 gene is another key player in the genomic landscape of sports medicine, primarily known for its role in glucose regulation and T2DM (56). KCNJ11 encodes the Kir6.2 subunit of the K-ATP channel in pancreatic beta cells, which is vital for insulin secretion (56). Much research, empowered by big data tools, has been conducted to understand the implications of the KCNJ11 gene in metabolic health and physical performance (57). A study by (57) explored the E23K variant of KCNJ11, highlighting its association with an increased risk of Type 2 diabetes. This finding is particularly relevant for athletes. Further research by (58) expanded on this understanding, examining the gene's impact on glucose control and insulin secretion. The insights gained from big data analytics are critical in understanding KCNJ11's function in glucose metabolism and can inform tailored nutritional and training programs for athletes.

The PPARG gene is also crucial in the context of sports medicine and genomics, particularly regarding its role in lipid metabolism and the development of metabolic disorders like obesity and T2DM (59). The PPARG gene encodes the peroxisome proliferator-activated receptor gamma, a nuclear receptor that plays a crucial role in adipocyte differentiation and glucose metabolism. Studies employing big data methodologies have shed light on the impact of PPARG variants on metabolic health, which can have significant implications for athletes. (60) identified a Pro12Ala variant of the PPARG gene, which has been found to be associated with a reduced risk of Type 2 diabetes. This discovery has important implications for understanding how genetic variations can influence metabolic pathways relevant to athletes, especially in sports where energy metabolism is a critical factor in performance. Additionally, (61) explored the function of PPARG in adipocyte differentiation and its role in lipid metabolism. In sports medicine, understanding the role of PPARG in lipid and glucose metabolism, facilitated by big data analysis, can inform individualized training and nutrition strategies for athletes, especially those predisposed to metabolic disorders. This gene's study highlights the growing importance of personalized approaches in sports based on genetic makeup.

The APOE (Apolipoprotein E) gene, specifically the APOE ε4 allele, is a significant genetic factor associated with lipid metabolism and cardiovascular health, with implications for both athletes and the general population (62). APOE is a protein involved in the transport of lipids and cholesterol in the bloodstream. Studies, many of which have utilized big data approaches, have investigated the role of APOE in lipoprotein metabolism and its genetic variations (62, 63). The APOE ε4 allele is associated with an increased risk of cardiovascular diseases, including coronary artery disease and atherosclerosis (63). Understanding an individual's APOE genotype, through big data-driven analysis, can be crucial in tailoring cardiovascular health management and preventive strategies. Knowledge of APOE variants can aid in assessing an athlete's cardiovascular risk profile, especially in sports that induce a high cardiovascular load. Athletes with the APOE ε4 allele may benefit from personalized preventative strategies to mitigate their risk, such as specialized training and nutrition plans aimed at maintaining cardiovascular health.

Thus, the special attention given to genomics in this article, centered on sports medicine and big data, is justified by the crucial role big data plays in deciphering and leveraging genetic information. This powerful combination of genomics and big data deepens our understanding of the genetic factors in sports performance and health.

5.3. Big Data and Metabolomics in Sports Medicine

As we advance into the future of metabolomics coupled with big data in sports medicine, a paradigm shift is at the horizon, one that holds the potential to fundamentally transform our approach to athlete health and performance optimization. This prospective vision is not just about incremental improvements but rather a comprehensive reimagining of how we understand and interact with the complex interplay of biological processes in athletes.

The convergence of metabolomics with big data has the potential to unlock unprecedented levels of personalization in athlete care (64, 65). Imagine a scenario where the metabolic profile of an athlete, derived from non-invasive samples like saliva or sweat, is continuously monitored and analyzed using advanced big data algorithms. This approach could lead to the identification of unique metabolic signatures that predict optimal training regimes, recovery times, and even susceptibility to injuries. For instance, a study by (32, 36) highlights how metabolite levels in rugby players offer insights into muscle turnover and dietary influences, underscoring the potential of metabolomics in personalizing athlete care.

Wearable technology, a fundamental component in contemporary sports medicine, is expected to increasingly incorporate metabolomics data. This integration promises real-time monitoring and dynamic adjustments to training and recovery programs based on instantaneous metabolic feedback. The advancements in wearable technologies and metabolomics will significantly enhance our understanding of the physiological mechanisms during exercise.

Longitudinal studies focusing on metabolomics will probably become invaluable, especially for managing chronic diseases. The application of metabolomics in sports medicine will also need to expand to include diverse populations (66, 67). This expansion will provide a broader understanding of metabolic responses across different demographics, leading to more inclusive and effective health and performance strategies.

A holistic multi-omics approach, integrating genomics, transcriptomics, and proteomics with metabolomics, will likely become the norm (66, 67). This comprehensive analysis will enable a deeper understanding of the complex interactions at play within the athlete's body, hence improve exercise physiology knowledge, but also potentially lead to more effective and targeted interventions.

As these advancements unfold, the enhancement of data analysis and interpretation tools will be crucial to exploit the full potential of big data in metabolomics. As the volume and complexity of data grow, so does the need for sophisticated analytical tools capable of extracting meaningful insights.

Collaborative research efforts, bringing together diverse expertise from sports scientists, data analysts, medical professionals, and athletes, will be key to realizing the full potential of this field. Such collaborations can foster innovative solutions and ensure that the advancements in the field are practical, relevant, and grounded in real-world needs. For achieving these exciting objectives, one shall consider several factors that will impact the outcome. Among the latter factors, data quality has to be optimal and consistent. This will require that (i) researchers across the globe gather and set the tone for standardized definitions and data collection (46); but also (ii) to take into account the context of data collection that may impact the outcome of epidemiological datasets (68). Towards these goals, one should consider an eventual change of mindset. Indeed, as suggested by (69) multicentric well-coordinated global studies will have to be performed. Our recent experience managing a high number of researchers from all continents shows that this is possible (70-72). However, our group has encountered some hurdles relative to some journals' editorial boards members or reviewers who are still reluctant to consider manuscripts with a high number of authors. As we are about to share and merge our data with the world of genetics, we believe that we shall inspire from this field and rather welcome international collaboration projects with a very high number of authors (73). The future of metabolomics may revolutionize how we approach athlete health and performance. It calls for a multidisciplinary and forward-thinking approach to fully exploit the benefits of this exciting convergence of science and technology.

6. Limitations

While this review provides an insightful exploration into the role of big data in sports medicine and exercise science, particularly focusing on wearables, genomics, and metabolomics, it is important to acknowledge that the scope and potential applications of big data in this field are far more extensive than what could be covered in a single article.

A thorough exploration in a book format might be more suitable to address the full extent and complexity of this subject.

One significant aspect not extensively covered in this review is the application of biomechanics analysis. Biomechanics, the study of the mechanical laws relating to the movement or structure of living organisms, plays a crucial role in enhancing sports performance and injury prevention (74). Integrating big data with biomechanical analysis could lead to breakthroughs in understanding the optimal techniques for various sports, the mechanics of injury occurrence, and effective prevention strategies. For instance, detailed biomechanical data can reveal insights into the most efficient movement patterns for athletes, reducing the risk of overuse injuries and enhancing overall performance.

An important limitation to acknowledge in this review is the challenge of data quality in big data research, particularly in sports medicine. Our experience, especially in epidemiological studies, highlights the variability in data collection methods across different research initiatives. This disparity can significantly affect the integrity and comparability of results. In sports medicine, where data collection often spans diverse environments and methodologies, establishing a standardized approach is crucial for ensuring consistency and reliability of findings. Moreover, the experience from large-scale, multi-centric studies, such as those during the COVID-19 pandemic, underlines the need for coordinated efforts and unified data collection protocols. These factors are imperative for the accurate interpretation and application of big data analytics in sports medicine and exercise science.

Furthermore, we have not deeply explored the field of transcriptomics in sports science. Transcriptomics, the study of the complete set of RNA transcripts produced by the genome, can offer invaluable insights into the molecular responses of athletes to training, stress, and injuries. Big data applications in transcriptomics could revolutionize personalized training programs and recovery protocols by providing a more nuanced understanding of an athlete's physiological response at the molecular level (75).

Proteomics, the large-scale study of proteins, is another area where big data could have significant implications in sports medicine (76). By analyzing protein expression patterns, researchers could gain insights into muscle adaptation, injury recovery, and the overall health status of athletes. Big data analytics could help in identifying specific protein biomarkers that are indicative of performance capacity, injury risk, or recovery status.

In addition, the integration of big data with other emerging technologies such as augmented reality (AR) and virtual reality (VR) in sports training and rehabilitation was not covered in this review. These technologies, combined with big data analytics, could provide more immersive and personalized training experiences, as well as innovative rehabilitation protocols. Lastly, while this review has highlighted some of the current applications and future potential of big data in sports medicine, it must be noted that the field is rapidly evolving. New technologies, methodologies, and insights are constantly emerging, which could further expand the applications and effectiveness of big data in this domain.

7. Conclusion

The exploration of big data in sports medicine and exercise science marks a critical shift towards a more nuanced understanding of athletic performance, injury prevention, and athletes’ health management. This shift, while focused on areas like wearables, genomics, and metabolomics, opens a new chapter in research, suggesting broader implications for the field. One of the key takeaways is the increasing importance of collaborative approaches. The integration of big data into sports medicine requires a synergy of disciplines from data science to biomechanics and beyond. This collaboration is essential for driving forward the innovative use of big data in enhancing athletic performance and health care.

Our review also pointed towards emerging trends where big data could play a transformative role. The development of more sophisticated injury prediction models, personalized training regimens, and rehabilitation programs tailored to individual athletes' needs are just the beginning. These advancements demonstrate how big data can lead to practical, tangible improvements in both athlete care and general health management. However, it is important to acknowledge the areas not extensively covered in our article, as outlined in the limitations section. The exploration of these areas represents an exciting frontier for future research, offering further opportunities for innovation and advancement in sports medicine. The sports medical community can continue to grow and advance by seizing these opportunities and exploring uncharted territories, ensuring that athletes and the wider public can benefit from big data. This technological innovation signifies a substantial progression in technology as well as a shift towards a more informed, effective, and comprehensive approach to sport performance and the athletes' health.

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Competing Interests

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