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Perspective

Precision Sports Science: What Is Next for Data Analytics for Athlete Performance and Well-Being Optimization?

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Abstract: In elite sports, athletic excellence demands meticulous performance preparation and a sound health status. This paper overviews the current propositions and applications of pervasive computing and data analytics and our vision on how they should be used in future frameworks to contribute to the optimal balance of athletes' performance and health requirements. Two main areas will be discussed. The first area is Sports Performance Optimization, in which we consider interesting recent advancements in data analytics for performance improvement, equipment design, and team member recruitment and selection. We will also briefly discuss how the betting industry has been relaying and developing sports analytics. The second area is Athlete's Wellness and Wellbeing, which will discuss how wearables and data analytics have been used to assess physical activity and sedentary behavior profiles, sleep and circadian rhythm, nutrition and eating behavior, menstrual cycles, and training/performance readiness. In the final part of this paper, we argue that a critical issue for managers to enhance their decision making is the standardization of acquired information and decision-making processes, while introducing an adaptable, personalized approach. Thus, we present and discuss new theoretical and practical approaches that could potentially address this problem and identify precision medicine as a recommended methodology. This conceptualization involves the integration of pervasive computing and data analytics by employing predictive models that are constantly updated with the outcomes from monitoring tools and athletes' feedback interventions. This framework has the potential to revolutionize how athletes' performance and well-being are monitored, assessed, and optimized, contributing to a new era of precision in sports science and medicine.

Keywords: data analytics; artificial intelligence; ubiquitous computing; wearables; sport science; athlete support

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1. Introduction

Sport analytics is a relatively new area that incorporates frequently disconnected analyses related to sports in general. It is important to acknowledge early in this discussion paper that the term "sport analytics" holds different meanings across the diverse spectrum of sports stakeholders. Initially, the adoption of sports analytics can be traced back to broadcasters, who recognized its potential in enhanced the viewing experience by providing deeper insights into performance metrics and player statistics. This not only enriched spectator engagement with specific sports or disciplines but also facilitated the understanding of performance dynamics. Such potential of sports analytics for performance evaluation and forecasting was rapidly recognized by sports managers and scouts. Its application has since expanded, becoming a staple in strategic sports management and talent scouting.

In the sport science area, statistics has been omnipresent since its emergence nearly a century ago. In contemporary research, robust statistical validation of findings is a prerequisite for publication in respected journals. The statistical principles have been adapted from fields such as medicine, social sciences, and humanities to meet the requirements of sports science. A common challenge in this regard is the reliance on small cohorts, a byproduct of specific selection criteria inherent to sports-driven studies. Unlike medical research, where extensive participant pools are often the norm, sports science frequently deals with limited cohort sizes and the restricted accessibility of individual data, complicating traditional statistical analysis. The introduction of data analytics into sports science represents a shift towards accommodating the inherent constraints and leveraging the potential of smaller, more specialized datasets. Despite its advantages, the integration of data analytics has been sporadic compared to conventional statistical methods. This paper aims to explore the reasons behind the underutilization of data analytics in sports science and to highlight the practical benefits of this approach, especially in scenarios where large group studies are impractical due to the elite nature of participants or confidentiality concerns.

As suggested above, there is a clear need for science-backed analytic tools that connect the knowledge pool of different sport science fields with the novel statistical techniques that produce reliable quantitative models. Additionally, such reliable tools need to focus on meticulous data collection and analysis, validate the outcomes to rigorously assess the strength and weaknesses of the proposed tools. Thus, the present work focuses on areas of importance in elite sports that are benefiting from the implementation of sport analytics, discussing the topic in three parts. First, for Elite Sports Performance Optimization, we showcase interesting recent advancements in data analytics for performance improvement, equipment design, and team member recruitment and selection. We will briefly discuss also how the betting industry has been relying and developing sports analytics. In the second part, Elite Athletes' Wellness and Wellbeing, we discuss how wearables and data analytics have been used to assess physical activity and sedentary behavior profiles, sleep and circadian rhythm, nutrition and eating behavior, menstrual cycles, and training/performance readiness. In the third and final part of this paper, we argue that a critical issue for managers to enhance their decision making is the standardization of acquired information and decision-making processes, while introducing an adaptable, personalized approach. We also present and discuss new theoretical and practical approaches that could potentially address this problem and identify precision medicine as a recommended methodology.

2. Elite Sports Performance Optimization

The astounding improvement of athletes' performance in the last few decades has brought the required levels of performance to the very limit of human abilities such as marathon running approaching the 2 h mark. The women's world records in the high jump from 1987 and the 400 m from 1985 serve as evidence of these boundaries.

Consequently, elite sport performance has, in effect, become the science of marginal gains, meaning that athletes need to be at their optimum to deliver on a particular occasion over a given period. The definition of optimum is not easy to provide as it is a dynamic state affected by numerous factors including training, health, and lifestyle.

The nature of each sport competition provides the framework for the definition of optimum performance. In sports where points are accumulated during an entire season, it is crucial to focus on building endurance at the pre-season to prepare athletes to overcome challenges posed by numerous competitions, time zone changes, and varying climatic conditions. As competitions approach, the focus shifts to refining sport specific performance parameters despite the ongoing challenge of managing inevitable performance fluctuations [1]. This is particularly evident in Olympic competitions for such sports, with tennis being a prime example where top-seeded players rarely secure the gold medal.

Moreover, it is essential to implement effective measures for monitoring and timely intervention, especially considering that athletes at their peak are often more vulnerable to viral infections, for example. The following sections below will highlight the most promising areas where data analytics facilitate the achievement of this optimum performance level.

2.1. Data Analytics for Performance Improvement

Data analytics have been predominantly used to interrelate the execution of different performance elements to a desired performance outcome. For example, there are numerous studies that correlate tennis player's body configuration to the speed and accuracy of the serve, or sprinters push from the starting blocks, and basketball free throws [2–6]. Although valuable, such results do not always provide clear guidance for performance improvement as they are result of a cohort analysis and may not benefit a particular athlete, even if a part of a cohort (for example if the athlete is a positive outlier). In short, researchers have been quite successful in establishing fundamental principles for effective coaching for the athletes' broad population but less successful in supporting the individual athlete (i.e., improving and fine-tuning their skills to reach their natural limit). Current progress in technology, wearables and especially artificial intelligence tools enable the facilitation of intensive and rapid feedback that in turn helps to deliver superior athletic performance. This is perfectly illustrated in this issue by the work of Cizmic et al. [7]. The work illustrates how smart equipment could evolve into an on-field assistant trainer with the help of sport analytics that become a part of a broader coaching system. The analytics are the backbone of the classification algorithm that is the heart of the system. This, we believe, is the future trend of the sport analytics implementation that would widen the access of less supported athletes to indirect expert support and would help them self-support and improve. It is a fascinating prospect that relatively low-cost equipment and software will help athletes with less access to funding for specialized staff to access proper support and stay competitive.

When the application of analytics is backed by rigorous science, it has the potential to deepen our understanding of execution techniques. Again, this is aptly demonstrated by Vives et al. [8] who show how performance analysis of tennis doubles serves is better understood by applying machine learning approach to identify key performance variables such as serve speed, serve angle, distance to sideline, and net clearance.

In both cases above, we see that in-depth knowledge of the respective sport is used to fine-tune and validate the outcomes from the software and achieve a high level of variability Some of those requirements are inherently contradictory as in some instances, performance improvement in terms of higher-level achievement could substantially increase the risk of injury due, for example, to increased mechanical loading on certain parts of the human body or alleviated physiological demands. Equipment design in sports like tennis, cycling and skiing underwent technological revolution that altered the performance and physical demands of athletes. On occasions, there were periods of high injury incidence as safety was sacrificed for performance. It is a well-known fact that the large new head of powerful tennis rackets curtailed the career span of several top-level players, notably highest-level female ones.

Equipment design has rapidly evolved with the continuous discovery and utilization of advanced materials, and new technology solutions and computer-aided design, while equipment selection is still shrouded in secrecy, and very little research has been published on its influence on specific performance and competition outcomes as well as associated injuries potentially attributable to the equipment in use. That is partially due to industry confidentiality rules, but one should not discount the sometimes-damaging effect of sponsorship that compels athletes to use specific brands that may not be the best fit for them. The authors carried out personal observations on sports like cycling, tennis, rowing, and ice track sports where selection is rigorously conducted utilizing performance analysis and proactive user feedback. Still, to the best of our knowledge, there is limited use of analytics tools and this area. The lack of published results and the confidentiality agreements prohibiting us from disclosing equipment data from our own research prevents us from providing more detailed analysis in the second part of this work that would then be used for informed decision making and assessment. What we have in the end is a system that allows us to progress further current knowledge and associated practices. Importantly, this includes such systems that can be used outside labs and bring athletes to actively participate in the process. Furthermore, with the help of these tools, athletes could work on their individual improvement with the support of a system that has the capability to detect both negative and positive developments without being overly prescriptive. However, success of such developments could only be achieved through proliferation across the respective sports to enable the creation of a large data base and most importantly, the publication of the results to ensure transparency and knowledge enhancement.

2.2. Equipment Design and Selection

Sport equipment design needs to satisfy three main objectives [9]:

- performance enhancement,
- safety improvement, and
- injury prevention.

Some of those requirements are inherently contradictory. For example, improvements aimed at achieving higher levels of performance can substantially increase the risk of injury due to increased mechanical loading on specific body parts or elevated physiological demands. In sports like tennis, cycling, and skiing, equipment design has undergone a technological revolution, transforming both performance levels and physical demands on athletes. This has occasionally led to periods of high injury incidence, as safety was compromised for enhanced performance [5,10–12]. It is well known that the larger heads of powerful tennis rackets have shortened the career spans of several top-level players, particularly among the highest-ranking female athletes.

Equipment design has rapidly evolved with the continuous discovery and utilization of cutting-edge materials, alongside innovations in technology and computer-aided design. However, the process of selecting equipment remains largely confidential, with minimal research available regarding its specific impact on performance, competition results, and injuries that may be linked to the equipment in use. This lack of transparency in equipment selection can be attributed in part to the confidentiality policies within the industry. Still, the potentially negative influence of sponsorships, which may obligate athletes to use specific brands not ideally suited for them, should not be overlooked.

The authors of this perspective have personally observed that in sports such as cycling, tennis, rowing, and ice-track sports, equipment selection is meticulously carried out through performance analysis and proactive user feedback. This rigorous approach ensures that the equipment chosen is optimally suited to enhance athletic performance and meet the specific needs of the athletes. For instance, in individual equipment selection, it's essential to pinpoint critical performance indicators and monitor them across various conditions and fatigue levels, as demonstrated in [13], though not at the highest level of performance. After establishing these key parameters, the corresponding design elements believed to influence performance are identified. A method akin to the design of experiments is then crafted, narrowing down to a select few combinations for trial. Athletes are asked to test these combinations without prior knowledge of the specifics, ensuring that the assessment of effects is both objective and supplemented by the athlete's feedback. Interestingly, this process sometimes necessitates adjusting parameters for varying conditions within a match, such as altering the string tension in tennis rackets or the shear stiffness of skis depending on snow conditions. One challenge encountered is that such adaptations may lead to changes in technique, potentially causing long-term issues.

Despite these insights, to the best of our knowledge, there is limited use of analytics tools in this area. The lack of published findings and confidentiality agreements that restrict the sharing of equipment data from our own research hinder a more detailed discussion in the latter part of this paper. However, certain high-tech sports, like ice track sports, demonstrate how equipment optimization can be fitted to the team's characteristics [14–16]. These examples show that equipment performance is not isolated from the athletes; adjustments in positioning, team lineup, and technical specifications should be considered collectively. This approach also facilitates adaptations to female anthropometry, enhancing performance while mitigating injury risks.

However, we still would like to point out that the integration of ubiquitous computing and wearable technologies with sports analytics can significantly boost our understanding of the interaction between athletes and their equipment, and its impact on performance and injury prevention. This topic is discussed in depth by Baca et al. [17], and the enhanced use of sport analytics will accelerate this development, highlighting how the advanced application of sports analytics can propel these improvements forward. We are convinced that the personalization and optimal selection of sports equipment and apparel hold the key to minimizing career-threatening injuries. Nevertheless, the field suffers from a lack of longitudinal research focused on the long-term effects on athletes, as the primary focus often remains on immediate outcomes rather than the overall impact.

It is certainly very difficult to convince both athletes and managers to compromise performance for the sake of safety or injury. Still, contemporary design methodologies that incorporate statistical principles at their core, such as the Taguchi method and principles of quality design, offer a pathway to a more balanced approach, provided that there are sufficient data to refine analytics tools. Once again, a major barrier is the lack of transparency, as the major goal of maintaining secrecy is a competitive advantage.

2.3. Betting Industry and Sports Analytics

The potential for performance analysis using sport analytics has been quickly noticed by sports managers and scouts, who are now widely using analytics for both assessment and prediction. It is intriguing though that the betting industry, despite being at the cutting edge of this field and experiencing significant growth and innovation, has been largely overlooked in academic research. The very nature of their business requires them to be ahead of the pack, necessitating the production of highly accurate performance predictions and comprehensive analyses of trends through advanced sports analytics and statistical methodologies [18].

The domains of broadcasting, management, and betting command the majority of investment in this sector, attracting a wide array of consultancies, startups, and well-organized consortia. These entities are dedicated to developing and advancing analytical tools tailored to their specific needs, which, in turn, has contributed to the controversial reputation of this sector. As in many other analytics applications, business have taken over unfinished research and implemented it commercially to a myriad of applications. It is notable that there are very few publications detailing the exact statistical methods implemented by the developers. The issue was perfectly captured by Szymanski [19] in his seminal work "Sport analytics: Science or alchemy?". Szymanski critiques the tendency among many developers to keep their methodologies secret, lacking transparent scientific evidence and support. His arguments are compelling and well-founded. Despite recent counterarguments from figures like Charles Mountifield [20], we agree with Szymanski's perspective that sports analytics tools should undergo rigorous and critical scientific evaluation to ensure their credibility and effectiveness.

2.4. Team Members Recruitment and Selection

Major sporting events like the Olympics, held every 4 years, have a significant impact on funding decisions by both public authorities and private sponsors. This creates a substantial responsibility for sports governing bodies to select athletes who have the highest likelihood of achieving top performances at these elite levels, sometimes even prioritizing this over an athlete's historical performance. The days of using simple elimination competitions to select representatives, where the best performers on the day were automatically chosen, are now behind us. Such methods, apart from being simplistic, do not support athletes' preparation adequately and are prone to legal challenges, such as from athletes unable to compete on selection day due to personal or health issues.

Consequently, most governing bodies have developed comprehensive selection policies tailored to specific sports, laying the groundwork for the application of sports analytics. These policies aim to establish a framework within which sports can identify athletes most likely to excel at a particular event. For those interested in cycling, this process is quite transparent, as top teams select leaders and members for specific competitions throughout the year, with athletes following specialized programs aimed at peaking for these events.

Although numerous analytics are employed behind these selection processes, there is no universally accepted approach. Analytics serve as tools to aid decision making rather than as the sole determinants. Ultimately, the decision often rests with the management, who may not be obligated to provide a rationale for their choices [21].

Le Gall et al. [22], over a decade ago, outlined several criteria for assessing performance, encapsulating the rationale for scientifically grounded selection processes and associated high-performance support programs. These principles have since evolved in practice and become integral to the management of team performance. Although initially devised with soccer players in mind, these guidelines are broadly applicable across most team sports. In short, the principles could be summarized as:

a. Creation of baseline profile: establishing a control or baseline profile for each team member involves a complex array of parameters, creating a multi-dimensional hyper-surface analogous to biological homeostasis, which also includes an athlete's baseline homeostatic state.
b. Monitoring wellbeing and health: Emphasizing the importance of athletes' health and psychological state, this principle acknowledges that athletes perform best when they are physically well and mentally unburdened. Neglecting this aspect can have severe consequences for an athlete's wellbeing.
c. Objective assessment of training interventions: This involves critically evaluating the effectiveness of training interventions, moving beyond dogmatic practices to individualized adjustments backed by quantitative analysis. The complexity of correlating interventions with performance outcomes necessitates a deep understanding of the underlying processes and the importance of peer input and review.
d. Tracking performance over time: analyzing performance fluctuations to identify potential causes is crucial. This multifactorial analysis considers environmental, physiological, psychological, health factors, and biological variances such as circadian rhythms, highlighting the need for rigorous and constant monitoring and analysis.
e. Aligning performance abilities with competition demands: This is controversial and often leads to friction and pressure on coaches and officials. Providing evidence-based constructive feedback can help mitigate the psychological impact on athletes. Although the analysis may still involve uncertainties, it can also provide coaches with the necessary confidence to boost their work.
f. Addressing deficiencies and enhancing strengths: Balancing the improvement of weaknesses and the enhancement of strengths is complex, as athletes' abilities are influenced by numerous factors. In some cases, weaknesses may hinder the development of strengths, such as a power athlete's lack of endurance affecting their ability to sustain high-intensity training.

Professional football, frequently called soccer, is one of the sports that invested most in the development of sport analytics and introduced them for various purposes, as the players are the most valuable assets of every club. Club managers have acknowledged the need for specialized care and support for these assets. As a result, progressive clubs have implemented measures such as sleep and nutritional monitoring, psychological support and assessments, among other commendable initiatives, to enhance player performance and wellbeing.

Consequently, a significant portion of the published research focuses on professional sports competitions, with limited information available about the procedures and practices in Olympic sports. This intriguing area of research is not explored in depth in the latter part of this work, as it falls outside our emphasis on models backed by rigorous science. Moreover, nearly all information pertaining to high-performance programs, including broad selection policies, is kept confidential. Experts in performance analysis make use of analytics to assist management bodies in forecasting the peak performance an athlete can deliver within a season, and in identifying any decline in form. These insights also aid in selection strategies supported by high-performance programs.

We believe that, for a principle, particularly within democratic contexts, that such information should be made public after a reasonable duration (i.e., one Olympic cycle), to promote open learning and the sharing of best practices. Maintaining secrecy does not serve the interests of rational and objective evaluation, and greater transparency could significantly benefit the field of sports analytics and athlete management.

Beyond organizing and evaluating athletes, there is a complex layer to their preparation involving their personal well-being outside of daily sports activities. This aspect is crucial not only for their current performance, but it also plays a significant role in their long-term development. The upcoming sections will dig into the personal dimensions of athlete support and development, exploring how this support can be customized to achieve the best possible outcomes. Tailoring support to individual needs is essential in addressing the holistic well-being of athletes, ensuring they are equipped both physically and mentally for optimal performance and growth.

3. Elite Athletes' Wellness and Wellbeing

In the pursuit of athletic excellence, elite athletes commit to meticulous physical and emotional preparation for competitive performance. However, the comprehensive well-being of athletes—encompassing physical, mental, and social dimensions—directly impacts their overall health and, consequently, their competitive performance. This means that a holistic view of athletes' health must contemplate integrally both the performer and the person [23]. This understanding evidences how complex and multidisciplinary sports performance is. Thus, addressing complex and multidisciplinary problems requires equally complex and multidisciplinary solutions.

From the performer perspective, it is well established that the relationship between training load, injury, and fitness shape athletes' journey to their best performance, and this is mostly dependent on the design of appropriate training programs [24]. Therefore, monitoring the training load, especially focusing on the load ratio that athletes are prepared for, is crucial.

Shifting to the person perspective, it is noteworthy that athletes spend a substantial portion—up to 80%—of their waking time in off-training activities [25]. Thus, there is an impact of athletes' lifestyles on overall wellness and wellbeing [26]. For example, physical behaviors including physical activity levels, sedentary behavior, and sleep make part of athletes' lifestyles and have been put in perspective to understand potential recovering strategies and health-related risk factors in these specific population. Furthermore, nutritional considerations play an important role in optimizing training adaptations, with eating behaviors representing a significant concern for athletes' health [27]. While ongoing debates surround the potential impact of the menstrual cycle on women's training adaptations and performance, it is evident that the health status of female athletes is linked to its characteristics [28].

Therefore, the examination of off-training time should reveal relevant information on aspects related to training adaptations and athletes' wellness and wellbeing. When integrated with training and competitive performance outcomes, off-training data should serve as a comprehensive screening tool, offering a nuanced understanding of the athlete as a whole. Despite the recent maturity of pervasive computing and data analytics applications in sports performance, capable of handling great amounts of information [17], there remains an ongoing discussion among academics and practitioners regarding the real use of data to inform training process decisions. While the technological capacity exists, we believe that existing gaps in information and decision support systems still affect the optimal level of personalization that can be achieved in predictive and prescriptive insights.

In the first part of the present paper, we identified off-training activities as directly related to wellness and wellbeing in athletes. We noted recent pervasive technologies and data analytics methods involved in the assessment and profiling of physical behavior profiles, sleep and circadian cycle, nutrition and eating behaviors, menstrual cycles, and readiness. In the second part, drawing inspiration from the healthcare domain, we explore how a precision medicine framework can be applied to help establish the standardization of performance/health descriptive with better diagnostics, as well as more personalized predictions and data-driven prescription abilities.

4. Current Off-Training Wellbeing/Wellness Profiling in Elite Sports

4.1. Physical Activity (PA) and Sedentary Behavior (SB) Profiles

Pervasive computing and data analytics play a central role in the quantification of physical behaviors as physical activity (PA) levels and sedentary behavior (SB), enabling their detailed description. The field of wearable intelligent systems, particularly those employing sensor-fusion technology, has fostered a successful commercial market dedicated to developing inertial measurement units and algorithms for event detection, as well as energy expenditure estimation in free-living activities—a field commonly known as actigraphy [29]. Guided by the World Health Organization's general recommendation, individuals should aim to accumulate at least 150 min of moderate-intensity aerobic PA, 75 min of vigorous-intensity aerobic PA, or an equivalent combination of both on a weekly basis [30]. These guidelines are designed to reduce mortality and bring significant health benefits for the general population. However, it is important to note that common perceptions might mistakenly overlook elite athletes as a group that presents healthy physical behaviors.

Numerous studies have already systematically quantified the amount of PA and SB presented by athletes across different sports, skill levels, age, and gender. Regardless, studies have shown that athletes are not necessarily physically active [31], but might achieve the weekly recommended amount of PA [32] and also report alarming levels of SB [32–35].

Mostly, athletes exhibit substantial amount of sedentary and light activity as well as prolonged sitting [33], surpassing the levels observed in non-athletes [34–36]. Physical behavior profiles are predictive to health risk factors independently on the amount of PA accumulated [37]. Despite athletes generally having higher longevity, particularly in endurance-oriented sports [38,39], it is essential to recognize that physical inactivity and excessive sedentary behavior are linked to the development of chronic diseases [40]. This underscores the importance of understanding and addressing the physical behavior patterns observed in the athletic population for comprehensive health management.

Balancing PA and SB off-training seems to be challenging. While passive recovery is acknowledged as a component of training programs [41], it also carries the potential to contribute to an overall lifestyle that may be detrimental to performance. For instance, an increased amount of sitting time has been linked to higher adiposity in athletes [42]. That said, one might question if there are any interventions that used pervasive computing and data analytics to manipulate and modify physical behavior profiles to improve performance and health. Despite successful assessments and profiling in the literature, there is a notable lack of intervention initiatives that target such changes [41]. A recent initiative has been undertaken to explore the effects of wearables' notification systems, incorporating tactile and/or visual feedback on the tracking of information related to PA and SB profiles. This approach, designed to influence users' behavior and mindset, has shown positive results for physically active individuals [43]. However, when applied to athletes, results indicated that the reminders to move did not influence their off-training physical behavior profiles or training responses [44].

Recognizing the limitations of standalone interventions, such as PA warnings from monitors, is crucial to encourage the adoption of a multi-component strategy. Coupling devices with social media-affiliated apps, including information feedback, social comparison, and goal-setting are potential options that have successfully increased the effectiveness of interventions in the general population [45,46]. Further research and innovation are needed to develop tailored interventions that consider the unique challenges and requirements of elite athletes.

4.2. Sleep and Circadian System

Sleep quality has also been brought to the center of the athletic recovery problem and health. Sleep is regulated by the circadian system and is classically viewed as an important part of the recovery process [47]. Deprivation of sleep leads to impaired brain function, impacting decision making in performance [48]. Furthermore, it is associated with metabolic problems [49], impairment of the immune system function, muscle repair, and might also stimulate overtraining symptoms [50], suggesting a broader impact on physiological health.

The relationship between sleep, recovery and performance is held by the sleep phase (circadian timing), duration, and quality [51]. A recent review has pointed out that both objective (sleep efficiency, latency, wake episodes and total wake episode duration using actigraphy) and subjective (Pittsburgh Sleep Quality Index, Likert scale, Liverpool Jet-Lag Questionnaire, and RESTQ) parameters are effective for monitoring sleep quality in sport [52]. Objective measures involve the use of wearable trackers that are accelerometer- and heart rate photoplethysmography-based. However, as highlighted in recent discussions [17], there remain significant challenges with the use of inertial measurement units and the algorithms embedded within them for accurately detecting critical sleep timepoints. Additionally, the restricted access to raw data from many of the leading sensor brands further complicates the depth of analysis and control over sleep patterns, posing a hurdle to optimizing sleep for athletic performance and recovery.

Despite the recognized importance of sleep, elite athletes often experience less total sleep than non-athlete counterparts, regardless of the type of sport [53]. Recent findings suggest that high to medium off-training PA, combined with medium to high training responses, may be associated with decreased sleep quality [54]. An interesting study proposed a statistical package incorporating unsupervised clustering algorithms to analyze athletes' sleep quality data from questionnaires. This approach allows for grouping athletes based on different characteristics, creating thresholds, and enabling a personalized approach to recommendations [55]. In this proposed method, athletes exhibiting poor overall sleep quality and concerning sleeping behavior are classified in the priority group. Recommendations for this group may include objective monitoring and the use of cognitive behavior therapy to alleviate pre-sleep anxiety. Athletes experiencing sleep disturbances linked to sleep routine and environmental factors would be suggested to undergo monitoring with diaries and interviews to identify the reasons behind bedtime and wake time inconsistencies. Athletes with low-priority scores would be advised to maintain their sleep habits, with periodic assessments. It would be noteworthy to explore the effectiveness of an intervention program based on this assessment method in transitioning athletes between high- and medium-priority groups to low priority. This could provide valuable insights into the impact of targeted interventions on improving sleep quality and overall well-being among elite athletes.

4.3. Nutrition and Eating Behaviors

Nutrition stands as an additional important factor influencing athletes' performance, wellness, and well-being. Ingested nutrients can play a crucial role in cellular signaling pathways that modulate muscle adaptations to both endurance and resistance training. For instance, the consumption of carbohydrates and ergogenic acids, such as caffeine, creatine, sodium bicarbonate, and beta-alanine, is recognized as integral to performance enhancement [27]. Additionally, dietary supplements are commonly used for various reasons, ranging from health maintenance to performance enhancement [56]. The concept of periodized nutrition is frequently emphasized as an optimization strategy to maximize performance. It involves a planned and purposeful use of essential micro and macronutrients tailored to enhance adaptations targeted by individual exercise sessions or periodic training plans [27,57].

Nutrition is a field rich in descriptive, prescriptive, and predictive knowledge, allowing for the individualization of responses to enhance sports performance. The literature offers a lot of recommendations considering, for example, endurance [50] or strength-dependent sports [58–60], or training session intensities and conditions [57], and the impacts of omnivorous and vegetarian nutrition in physical performance [61]. While there is a wealth of knowledge in the literature, the integration of big data analytics and pervasive computing for facilitating access and monitoring in the field of sports nutrition is yet to find its appeal in sports. Some of the few studies in this area have employed machine learning algorithms for image detection and recognition. For instance, the NutriNet network architecture was introduced as a solution for food and drink image detection and recognition, employing deep convolutional neural networks. Initially designed for the dietary assessment of Parkinson's disease patients [62], this technology showcases the potential for leveraging machine learning in nutritional monitoring. In addition, the automation of remapping over 4000 unique food items onto food composition tables has been explored using fuzzy matching and machine learning approaches. This method, achieving a precision of 88.75%, demonstrates the potential of data-driven approaches to streamline dietary intake quantification and analysis [63].

As wearables and data analytics continue to advance, there is significant potential for innovative solutions to further optimize athletes' performance, wellness, and well-being through personalized and data-driven nutritional strategies. One critical aspect that can benefit from these advancements is the control for doping on ingested substances. Athletes must remain vigilant about the safety and allowance for drugs and supplement use in accordance with Anti-Doping Agency policies. Data-driven approaches to monitor dietary intake can play a role in compliance with anti-doping policies by analyzing nutritional patterns, ensuring adherence to regulations. This not only supports the integrity of athletes but also serves as a proactive measure to safeguard their health and well-being.

Low energy availability (LEA), an inadequate balance between an athlete's nutritional energy intake and the energy expended in exercise [64], is a relevant issue to diet and eating habits. It can give rise to a syndrome known as relative energy deficiency in sport (RED-S), resulting in impaired physiological functioning of the body. RED-S manifests as metabolic rate disturbances, menstrual irregularities, compromised bone health, weakened immunity, impaired protein synthesis, and cardiovascular issues [65]. Recent studies showed that the prevalence of RED-S ranges from 22% to 58% across various sports (i.e., athletics, combat, horse racing, rowing, cycling), impacting both male and female athletes [66,67]. The multifactorial nature of the syndrome involves risk factors such as eating behaviors or diagnosed eating disorders, the pursuit of body composition goals for weight loss, high energy demands of training programs, mismatched energy intake, and lack of financial resources for dietary needs [68]. However, the literature highlights the difficulty in screening due to a lack of valid guidelines for diagnosing RED-S and LEA [64,67,69], as well as the absence of normative values to differentiate individuals with the syndrome from 'healthy' peers [68], particularly in free-living conditions [68].

Pervasive computing through wearable technology, including smartwatches and proximity sensors, has emerged as a promising avenue to address eating behavior issues associated with hand-to-mouth gestures during food and beverage consumption in free-living conditions. Data-driven approaches for classifying behaviors have shown encouraging results in this domain [70–72]. An interesting example involves the utilization of inertial sensors embedded in smartwatches to detect food intake events, such as bites, throughout the day. This was achieved through an end-to-end Neural Network (NN) framework with both convolutional and recurrent layers [73]. Authors achieved a 0.91 F1 score for detection, which is a very good result for the fraction of true positive records among the total of actual positive records. However, a limitation of this approach is the real-time execution due to the availability of on-chip AI support that can effectively provide real-time performance.

An additional approach that can be interesting for monitoring off-training behaviors is presented by [74]. In their work, momentary changes in heart rate variability were used to detect the risk of episodes in adults with clinical emotional eating via a photoplethysmography wrist-worn sensor (Empatica E4, Cambridge, MA, USA). Applying machine learning methods, the Support Vector Machine models on signal frequency domain features achieved a classification accuracy of 78%, sensitivity of 79%, and specificity of 75%. While improvements in data recording and signal processing are needed to enhance classification success rates, the feasibility of such methods in identifying episodes in elite athletes remains uncertain.

Indeed, there are conceptual challenges to overcome, especially in the relatively new and nuanced concept of emotional regulatory skills associated with eating behaviors, which currently lacks predictive and discriminative validity [75]. Despite these challenges, the importance of 'real-time' eating behavior detection for syndromes diagnosis is evident. It is known that the early identification of unhealthy patterns, coupled with education, prevents long-term conditions such as RED-S and LEA, particularly considering athletes' tendencies to underestimate their perceived intake [64]. Hopefully in the near future, enhanced applications of data-driven methods to classify eating behaviors in athletes will be able to give feedback not only to educate the athletes, but also to support the professional staff management of athletes at risk.

4.4. Menstrual Cycle (MC)

The MC stands as a valuable health marker in female athletes and is also considered in relation to training recommendations. Health-wise, menstrual dysfunction is linked to a diminished quality of life due to increased anxiety, fatigue, and pain interference [76]. In terms of performance, female athletes perceive that the MC impacts it [28,77,78], as a few studies have reported changes in muscle strength [79] and peak power performance [80] related to the changes in the reproductive hormones including testosterone.

Recent challenges have been raised against resistance training recommendations based on the MC, citing methodological shortcomings. Criticisms emphasize the lack of robust evidence supporting the claim that training during the follicular phase is more efficient compared to the luteal phase [81]. Most reviews in this area [76,81–83] highlight issues such as small sample sizes, failure to measure female sex hormones to confirm the MC phase, and inconsistencies in determining the phase, among other confounding factors in the reviewed studies.

Therefore, addressing these methodological concerns is crucial for providing reliable and conclusive insights into the relationship between the MC and athletic performance. Currently, MC monitoring can be accomplished through various methods such as calendar-based counting, basal body temperature recording, and tracking technologies. The use of smartphone applications, for instance, has become popular for predicting menstrual phases based on unsupervised machine learning algorithms, with predictions improving over time as users track their data. However, studies have shown that predictions from these apps often deviate from the real period dates, ovulation day, and fertile window, indicating the need for improved accuracy [84,85]. Achieving accuracy in MC tracking seems inherently challenging, as studies indicate that fewer than 20% of mobile app users have a regular 28-day cycle [86]. Urine hormone testing devices are considered the gold standard [87], and monitoring basal body temperature, cervical mucus, cervix position, and vaginal sensation (the Fertility Awareness Method) [88] might also help with determining the MC phases.

The current use of menstrual cycle (MC) trackers is primarily motivated by interests in diagnosing diseases such as polycystic ovary syndrome and endometriosis, as well as for family planning purposes [89]. In female athletes, not only has their psychological well-being been found to correlate with MC in performance [90], but menstrual dysfunction has been associated with RED-S [69]. Thus, there is an emerging opportunity to leverage tracking methods for unveiling the detailed aspects of the connection between MC, wellness, and sports performance, particularly since existing practices rely on self-reported, non-validated questionnaires [91].

4.5. Performance/Training Readiness

Athlete self-reported measures (ASRM) stand out as the most popular tool to assess the outcomes of interventions on athlete's health and well-being. These measures are questionnaire-based and typically cover subjective aspects such as mood disturbance, perceived stress and fatigue, muscle soreness, energy levels, and readiness to perform [92,93]. ASRMs are also claimed to reflect acute and chronic training responses in athletes' well-being [94]. However, the literature has raised concerns regarding the interpretation of these measures, citing a lack of conceptual and practical validity [23,95,96].

The ability of ASRM to predict performance or readiness to perform has been recently explored using different approaches. For instance, Alexandersen et al. [97] conducted a study on female football and found no significant relationship between wellness-related measures and match performance outcomes, using a linear regression model derived from a performance analysis company. However, when the focus is on predicting the ability to perform in matches or training sessions, wellness variables appear to play a significant role. Wiik et al. [98] and Kulakou et al. [99] achieved positive results when applying machine learning methods to predict readiness to play in footballers. Both studies used subjective self-reported wellness parameters from mobile ASRM, including readiness, mood, stress, sleep quality, fatigue, and soreness. The models were trained using team and individual data to predict the readiness of individual players. In both studies, training the model on team data but predicting for a specific target player achieved scores above 0.90, with higher accuracy for teams that had a greater volume of data collected. Daily predictions outperformed long-term predictions, such as weekly assessments.

Monitoring wellness and training load in elite athletes is a complex task, and current athlete self-reported measures (ASRM) methodologies still have room for improvement to enhance efficacy and usefulness. While there are examples of validated multi-item questionnaires developed for athlete assessment [100,101], their use might be tedious and fatiguing for athletes, affecting usability. The practical implementation of ASRM in sports organizations often involves custom-made assessments, [102], and surprisingly, over 45% of them are single-itemed. Most of these assessments have not been validated, and modifications from the originally non-validated items are common in practice [96]. With the development of mobile applications for ASRM, there is a certain excitement to strengthen its use as a monitoring option for elite sport due to its low financial investment and staffing expertise [103]. However, the overall quality of current ASRMs is debatable and should be carefully considered before implementation. This highlights the need for careful consideration and validation of ASRMs used in sports settings to ensure their reliability and effectiveness.

5. Future for Individual Profiling in Elite Sports: An Athlete-Centered Analytics Approach

To effectively handle the diverse aspects of wellbeing/wellness profiling altogether with performance of elite sports, information systems are irreplicable. A recent review summarized global providers that offer products capable of managing match, medical, load, training, scouting and more, and make them available to the different users in sport organizations/clubs [104]. Only three products were identified as being specifically designed to be used by individual athletes or group management systems, with data from different fields and control aims. This suggests that there may be limited options for sports organizations seeking comprehensive solutions tailored to the management of athletes' diverse data and highlights a gap in the market. Additionally, the observation that most sports information systems lack flexibility in manipulating their data models and do not adequately cover medical-related information signals a need for improvement in the current landscape.

We believe that the limitations identified in current information systems reflect limitations that the fields of health and sports sciences have in balancing standardization and individualization for decision making processes. While efforts are made to identify more precise variables and protocols to represent wellbeing and wellness in an athletic context and establish guidelines and frameworks, we acknowledge that personalized interventions enhance performance outcomes. Thus, the challenge lies in achieving an integrative and individualized approach, with objective assessments guided by athlete-centered analytics. Pervasive computing and data analytics have demonstrated the potential to offer valuable solutions. However, perhaps the missing piece to seamlessly integrate these two powerful instruments is a sophisticated framework capable of addressing the standardization–individualization issue.

In this context, Houtmeyers and colleagues [105] proposed a structure for the hierarchical organization of the elite sport data to facilitate decision-making in four steps: descriptive analytics, diagnostic analytics, predictive analytics and prescriptive analytics. Descriptive analytics require storing information on relevant variables or performance indicators that describe events during the training process. Diagnostic analytics aim at a comprehensive interpretation of these indicators. Predictive analytics forecast whether the expected outcomes from the training process will occur, allowing for a predictive analysis. Finally, prescriptive analytics identify the optimal, most efficient, and controllable strategy that can balance the probability of different training process consequences, such as performance improvement and injury risk. This theoretical work is relevant for the standardization problem related to training and performance status; however, it is still missing individualization.

One interesting approach that joins both aspects in the medicine/healthcare domain is precision medicine, leveraging data analytics tools to continually develop clinically relevant models for more precise therapeutic decisions [106,107]. The precision medicine process develops a dataset of different types of data/information on patients from medical history and lifestyle, to physical examination and laboratory diagnostics, imaging outcomes, immunology, and omics status. In elite sports, performance/training-related data (i.e., internal and external loads, and match outcomes) and wellness and wellbeing-related data (i.e., physical behaviors, sleep, nutrition, menstrual cycle, and others) would be part of the dataset. This dataset undergoes pre-processing to ensure quality and is then statistically analyzed using techniques such as clustering to pre-select relevant variables. As such, it would be possible to find proper standardization of the relevant information to describe and assess athletes' health and performance status. The next stage is to develop models using machine learning approaches, combining multiple predictors for specific clinical outcomes (e.g., disease onset, mortality) to diagnose or prognose. Critically, the developed models need refining to reliably predict the response of individual patients to treatment. These processes yield additional insights into disease and treatment, which are used as feedback to enhance the precision of the framework.

The novel aspect of precision medicine is the continuous update of biological, clinical, and statistical evidence to support clinical decisions. This is key to achieve a higher level of individualization and accuracy. We believe that data-driven decision making systems and frameworks in elite sports should also care about athletes' individual responses related to performance, training loads, and off-training wellness/wellbeing; using theis information as a feedback loop to refine the prediction models. This constant update places the individual athlete in the center of the whole process, and truly allows for the management to tailor the interventions with a higher level of precision.

6. Conclusions and Future Perspectives

The pursuit of athletic excellence demands a comprehensive approach to athletes' performance in alignment with well-being, thus considering physical, mental, and social dimensions. The examination of off-training factors such as physical activity, sleep, nutrition, menstrual cycle, and training readiness reveals challenges and opportunities. Pervasive computing and data analytics offer groundbreaking tools to quantify and analyze these factors, providing insights to enable the design of personalized interventions. The current state of off-training profiling highlights the need for validated methodologies, especially in areas like menstrual cycle tracking and athlete self-reported measures.

The complexity and multidisciplinarity involving performance and wellness/wellbeing requires equally sophisticated solutions. Looking ahead, an athlete-centered analytics approach is advocated, emphasizing the importance of individualized assessments within a standardized framework. We believe that one promising solution is to integrate pervasive computing and data analytics to profile elite athletes inspired by precision medicine principles in a sports analytics approach. It proposes a four-step process—descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics—to achieve a structured organization of information, but continuously correlating this structure with athletes' individual responses. This iterative process places athletes at the core, allowing for precise interventions tailored to their evolving needs.

In summary, we believe that the integration of pervasive computing and data analytics, guided by an athlete-centered analytics approach, holds great promise for advancing the understanding and management of health and performance in elite sports. As technology evolves and methodologies mature, the envisioned framework has the potential to revolutionize how athletes' well-being and performance are monitored, assessed, and optimized, contributing to a new era of precision in sports science and medicine.

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