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Sports Injury Forecasting and Complexity: A Synergetic Approach

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Abstract

The understanding that sports injury is the result of the interaction among many factors and that specific profiles could increase the risk of the occurrence of a given injury was a significant step in establishing programs for injury prevention. However, injury forecasting is far from being attained. To be able to estimate future states of a complex system (forecasting), it is necessary to understand its nature and comply with the methods usually used to analyze such a system. In this sense, sports injury forecasting must implement the concepts and tools used to study the behavior of self-organizing systems, since it is by self-organizing that systems (i.e., athletes) evolve and adapt (or not) to a constantly changing environment. Instead of concentrating on the identification of factors related to the injury occurrence (i.e., risk factors), a complex systems approach looks for the high-order variables (order parameters) that describe the macroscopic dynamic behavior of the athlete. The time evolution of this order parameter informs on the state of the athlete and may warn about upcoming events, such as injury. In this article, we describe the fundamental concepts related to complexity based on physical principles of self-organization and the consequence of accepting sports injury as a complex phenomenon. In the end, we will present the four steps necessary to formulate a synergetics approach based on self-organization and phase transition to sports injuries. Future studies based on this experimental paradigm may help sports professionals to forecast sports injuries occurrence.

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Key Points

The forecasting of sports injury requires the use of a synergetics approach based on principles of self-organization and phase transition in complex systems.

The four steps necessary to implement a synergetics approach to sports injury forecasting are: defining the time scale of the investigated sports injury; defining the order parameters that characterize the state of the sports injury system; establishing protocols that capture the time evolution of the order parameter(s) with a resolution sufficient to describe the dynamics of the system; and selecting methods to analyze the captured dynamics and forecast future states.

1 Introduction

In the last decades, much has been done in terms of applying complex systems approaches to sports. Research on the dynamics of collective behaviors in team sports [1, 2], decision making in sports [3], training methods for optimizing individual and group learning [4], and on complexity analysis of sports performance [5, 6] have reinforced the understanding that the philosophy and tools of a complex system approach have an essential place in sports. Only more recently, sports injuries have been recognized as a phenomenon that also should be studied from a complexity perspective [7–15]. In this perspective, many different approaches have been suggested to investigate sports injuries. These approaches include computational methods, such as agent-based and system dynamics modeling [12, 13], machine learning approaches (e.g., classification trees) [17, 64, 65], and neural network techniques [16]. A common ground of these approaches is the attempt to understand the contribution of many biomechanical, physiological, social, psychological, and environmental factors to injury causation. A frequent goal of complex systems' approaches that is still to be effectively achieved is anticipating an imminent sports injury (i.e., injury forecasting), which would allow actions to prevent such injury. Most of the current complex systems approach in sports must make some a priori assumptions about the factors and causal relationships that could be related to injury occurrence [12, 13]. However, within the field of complex sciences, approaches based on the physics of non-linear dynamics have been proposed to study complex systems without the need to make assumptions about the nature of the contributing elements. Recently, such approaches have been theoretically introduced in the sports injury literature [14, 17]. Potentially, these approaches may also have an essential place in the study of sports injuries.

According to the complex systems theory and, more specifically, the physics of self-organization, a sports injury can be conceptualized as an emergent phenomenon. As such, it could be studied under the same theoretical reasoning as other self-organizing phenomena. The physics of non-linear phase transitions (e.g., sudden changes in the behavior) in complex systems, in the tradition of Eugene Yates [18], Ilya Prigogine [19], Arthur Iberall [20], and Herman Haken [21], offers tools and concepts that may help sports scientists to investigate sports injury under this paradigm. More recently, Scheffer et al. applied similar concepts to study many phenomena in nature and society to identify early signals of critical transitions in complex systems [22, 23]. The identification of imminent transitions is the basis for a forecasting program for sports injuries. To fully appreciate the contribution

of this approach to the investigation of sports injury, one has to accept the principles of complexity and look to the emergence of injury from a different perspective. This approach will require an experimental paradigm shift that will push us, as a research community, to look for new forms of data collection and analysis. In this manuscript, after introducing key concepts related to complex systems based on the physics of self-organization, we will demonstrate the consequences of accepting sports injury as a complex phenomenon that could be anticipated. In addition, we will introduce the science of synergetics as a theoretical and methodological approach to study complex systems and identify early signals of critical transitions. Finally, we will describe the required steps to formulate such an approach to sports injury forecasting. The proposed approach may ultimately help sports professionals to improve their ability to forecast sports injury occurrence.

2 The Nature of Complex Systems

Complexity is present in all areas of science that deal with systems that evolve and change over time. Complex systems are dynamic, non-linear (i.e., the output is not directly proportional to its input), open systems (i.e., systems that exchange matter, energy or information with its surroundings) [24]. As a result of complex non-linear interactions among their comprising elements and due to the existence of recursive loops (or circular causality), complex systems are posed with uncertainty and can spontaneously organize themselves to generate emerging properties (self-organization) [9]. These characteristics are well described in the sports injury literature [9, 13, 25]. One characteristic that is always referred to as essential for identifying a complex system is that it is comprised of many elements [26–28]. However, the existence of a large number of elements that do not interact or interact in a simple manner does not define, by itself, a complex system [26]. Systems composed of many elements that interact regularly and predictably, and whose functions result from the sum of the properties of these elements, are considered complicated and not complex systems [26]. An example of a complicated system is a jet plane engine; it has many parts, but by no means is a complex system. In a complex system, all the existing elements interact in multiple and non-linear manners, producing new elements, functions, or properties, which are different from the sum of the parts that constitute the system [29, 27] (Fig. 1). Examples of such systems include stock markets, global climate, living organisms, and social interactions. As a result, it is possible to study complex systems by focusing on the topographic features of these systems, without the need to investigate the system's elements [21, 30, 31].

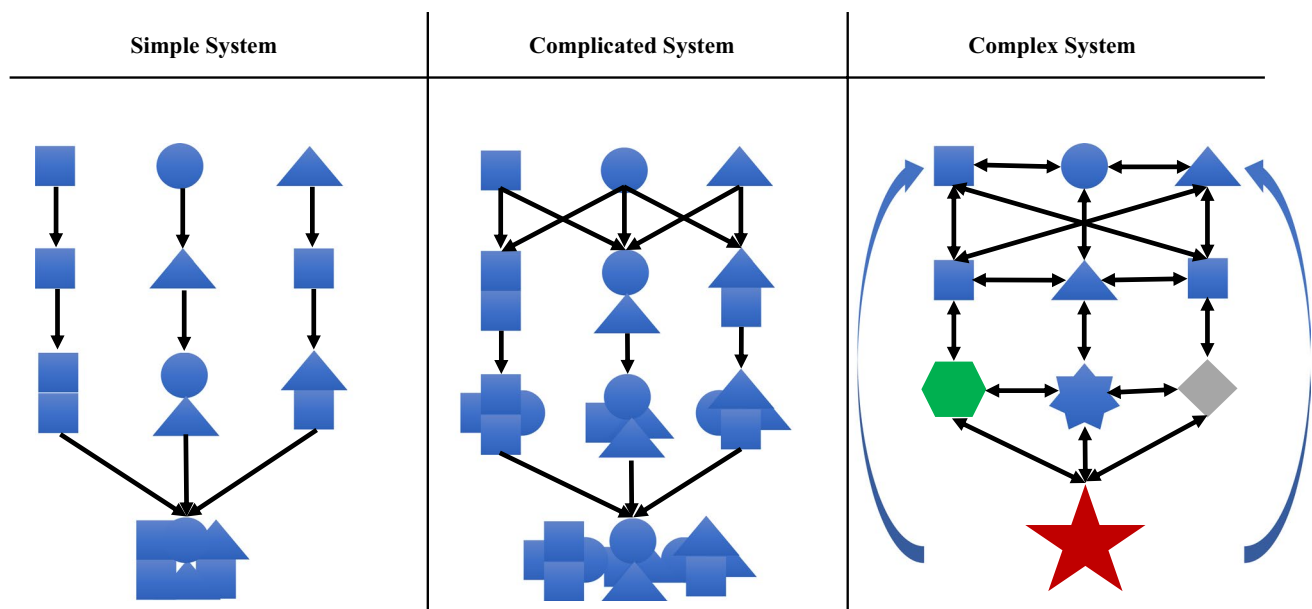


Fig. 1 Different types of systems. In the simple system, parts do not interact and the outcome is the direct sum of the parts. In the complicated system, simple interactions occur and many more elements produce the outcome. However, the outcome is still the sum of the parts. In the complex system, complex interactions among elements produce an outcome that is different from the parts (exemplified by

the different colors). In the complex system, the star represents the emergent outcome and the intermediate symbols represent the states that are dependent upon the interactions with the other elements. The outcome also affects the behavior of the elements (see recursive arrows). In this system, the outcome cannot be predicted by its basic elements

In sports, the process of injury occurrence depends on many factors or constraints that interact in ways that are frequently unknown [9, 14]. For example, hamstrings injuries can be described as the result of interactions among factors such as flexibility, strength, core stability, fatigue, previous injury, and architecture of the musculoskeletal system [32]. When investigating a complex phenomenon, the investigator may select the scale that best describes the problem to be studied. However, the fact that a hamstring injury could be related to the athlete's capabilities by no means precludes the existence of socioecological factors. Since, in a self-organizing phenomenon, many factors at different scales are present, psychological, social, and environmental factors also interact with biological factors towards the occurrence of hamstring injuries [33, 14]. Individually, each of these factor's expression depends on the interaction with multiple factors, creating complex relationships [9]. Strength, for example, is not a simple element, as its contribution to hamstrings injury could be affected by fatigue, sleep habits, psychological status, and nutrition. Thus, the understanding of sports injury etiology requires the consideration of many complexly organized factors. In Fig. 1, the green hexagon could represent muscle strength, for example, as its contribution to the emerging outcome is also dependent upon the interactions with other elements (e.g., fatigue [34]). In this same figure, the red star could depict a hamstrings injury, as it is

the emerging phenomenon that results from the complex interactions among many elements.

Another feature of a complex system is that the current status of a system is dependent upon previous states and initial conditions (history dependency) [35]. Obtaining information about single states does not truly inform on the system's dynamics and does not allow an understanding of the future states of the athlete. A single evaluation of strength does not tell the story about an athlete's strength during the injury onset. Therefore, pre-season, inter-season, or post-season assessments cannot provide a full description of the athlete's condition, as they refer to single states only. Despite the methodological difficulties imposed by the assessment process in sports, to study a complex system, we need to have data from multiple time points, preferably continuous, to get detailed information about its global behavior.

In addition to history dependency, we must recognize that the intricate relationships among elements and the ever-present context variability in complex systems could render standardized models of sports injuries and simple predictions ineffective. Due to the dynamic nature of complex systems, sports injuries cannot be understood or predicted solely based on the contribution of a few elements. To confidently apply the concepts of the physics of non-linear dynamics to study complex systems and identify early signals of future manifestations of injuries (forecasting), it is necessary to recognize that we do not know all the factors

involved in the process of injury occurrence. In fact, even if we knew all factors involved in the injury process, we would still not be able to fully understand it, as we would not have access to all emerging interactions among factors and constraints and the system's initial conditions [36, 27].

2.1 The Consequences of Adopting a Non-Linear Complex System Approach to Sports Injury

At this point, a valid question to be asked is: "What do we gain by recognizing the injury process as a complex phenomenon if such phenomena cannot be fully understood or explained?" The crucial point is that, although a complex system is difficult to predict and cannot be entirely described by its parts [37], such a system is still governed by laws. The multiple elements observed at a specific level (e.g., microscopic level) give rise to much simpler behaviors at a higher level (e.g., macroscopic level) [38, 39]. This phenomenon is an example of self-organization, in which the seemingly chaotic and unpredictable behavior of the system at one scale produces ordered behavior on a higher scale [31]. Similarly, an emergent macroscopic pattern influences the behavior of the parts (e.g., at the microscopic level), as an example of a recursive loop in complex systems (see Fig. 1) [9, 40].

In the context of sports injuries, the process of injury occurrence also results from the collective contribution of many variables and can be understood as an emergent phenomenon of a complex system [9, 14]. Human performance requires the contribution of many body systems, such as the musculoskeletal, respiratory, cardiac, and neural systems. These systems must cooperate among themselves to deal with the requirements of the sport and with the environmental constraints imposed on them. Also, social and emotional pressures may alter how these systems interact and ultimately affect performance. It is well known that coach and investor pressures are vital factors related to how the athlete emotionally handles his/her training schedule and obtains success [41]. However, how these pressures affect the athlete may be dependent on the individual's history, which is related, for example, to previous injuries or experiences [10]. Therefore, treating the process of sports injury and performance as emergent phenomena of a complex system seems to be a proper approach [9]. Assuming complexity in sports injuries is to assume self-organization. Thus, one possible approach to be used by sports scientists who attempt to forecast sports injuries is to capture and understand the system's high-order behavior, which requires us to adopt the proper tools and methods normally used to investigate self-organizing phenomena. Among different perspectives on the physics of non-linear dynamics, one that has been successful in investigating self-organization in complex systems is synergetics [21, 42]. Synergetics investigates any phenomenon topographically, focusing more on 'what' and 'when' than

on 'how' it happens. What happens may include observable events that can anticipate an upcoming critical event. The existence of these early signals allows us to forecast the critical event and provides the opportunity to establish mitigating actions before it happens ('when'). The 'why' rests on the avoidance of instabilities that occur when the parts can no longer sustain their ongoing dynamics. Perhaps this approach also has an essential place in the investigation of the emergence of sports injuries.

3 Applying Synergetics to Sports Injury Investigation

Synergetics studies how the cooperation among many elements acting at a lower level (e.g., microscopic level) leads to the emergence of new states (structures or functions) at a higher level (e.g., macroscopic level) [21, 42]. This emergent organization seen at a higher level is frequently called a *high-order* behavior. In turn, high-order behaviors will also influence the behaviors and interactions at the lower levels (i.e., recursive loop or circular causality, see the complex system in Fig. 1) [42]. These emerging states are captured by high-order variables, also known as *the order parameters*, which are formed by the collective behavior of the systems' elements, and, therefore, can be used to describe the system's dynamics [21]. The high-order (e.g., macroscopic) organization is steered among different states according to a few parameters, the *control parameters*. When one or more control parameters change, the system's behavior may slowly adapt (e.g., gradual performance improvements) or, when it reaches a critical level, may exhibit abrupt changes (phase transition) that lead to the emergence of states that are qualitatively distinct from the previous states (e.g., injury occurrence) [43, 42]. For example, factors such as training intensity, increased training frequency, or modifications of other psychological and physiological constraints related to the athlete's performance may induce major qualitative changes in the observed movement pattern (order parameter). In this sense, fluctuations of the order parameter, which happen while the control parameter changes, can be monitored, and, when the fluctuations increase, they can be used to identify the imminence of a critical state transition (see Table 1 for definitions).

In sports, during training and competitions, the athlete undergoes a continuous process of change in the status of the musculoskeletal, neural, cardiovascular, and endocrinal systems and in environmental, social, and psychological variables. These changes modify the general athlete's condition (e.g., physical conditioning, general health), and produce fluctuations in behavior (small variations in movement patterns) that may help the athlete to explore and discover more stable and successful solutions (e.g., better movement

Table 1 Definitions of synergetics terms

Term	Definition	Sports example
Synergetics	An interdisciplinary field that studies the process of cooperation of many interacting individual parts that leads to the emergence of spatial, temporal, and functional structures	Area of investigation of processes such as injury emergence, collective behaviors in teams' sports (cooperation among athletes), decision making in games, learning, and performance improvement
Emergence	A process that generates patterns that arises from the collective actions of many elements. These patterns possess properties that are different from the properties of the individual elements	Organization of players during a match, athlete's decision in sports, goal/scoring during games, injury during sports practice
Self-organization	A process in which a new order emerges in a system from local interactions among parts, without specific interference from outside sources or internal instructions	The process that leads to the emergence of injury as a result of many physical, physiological, psychological, social and environmental constraints
High-order variables	A variable that is a compound of simpler variables or variable that is in a scale superior from others. A high-order variable can be an order parameter	Heart rate variability as a variable that indexes the contribution of many other variables related to the autonomous cardiac system
Order parameter	Also known as the essential or collective variable, the order parameter is the mode of organization revealed by changes in the control parameter that characterizes the states or the dynamics of a system through fewer high-order variables than the number of the system's basic elements	Higher order variables used to evaluate physiological responses to exercise, such as HRV and perception of effort, movement coordinative measures such as relative phase, or complex time series variables such as entropy or fractality
Control parameter	Parameter, generally external to the system, whose changes lead to qualitative changes in the behavior of the system as captured by the order parameter	Training intensity, training frequency, cumulative stresses, mental/social pressures in sports ^a
Phase transition /critical transition	Defines the point at which a transformation between states occurs (e.g., states of matter: gas, liquid, and solid). In synergetics, it refers to the critical points, where the behavior of the system changes qualitatively on the macroscopic scale (critical transitions)	An abrupt change in the state of sports-related systems: injury occurrence, loss of player's mental concentration during matches, team's morale change during a season
Fluctuations	Random deviations of a system from its regular state. A critical fluctuation defines the point at which the increase in fluctuations within the system leads to a phase transition	Movement pattern variability, variability of game performance, variability in force output ^b
Enslaving principle	The principle by which the order parameter, once created, governs the behavior of the parts that compose the system	Circular causality in sports, such as training load improving physical capacity, but existing physical capacity being necessary for the athlete to endure training load ^b
Critical slowing down	The time required for the system to return to its equilibrium state (reduced fluctuations) after a perturbation tends to infinity, showing the increasing instability of the system	In a fatigued state the athlete may not be able to produce stable movement patterns, decrease his/her capacity to resist perturbations and become more susceptible to injury ^b

^aTo be control parameters, these variables should be capable to induce changes in an order parameter

^bTo be valid, these examples/variables must be related to an order parameter

patterns or more efficient performance) [9, 14, 44]. In general, some level of movement variability (fluctuations) is beneficial, since it is related to a more efficient and flexible movement pattern [45, 44]. However, when one or more control parameters (probably related to training, recovering, or adapting factors) reach a critical value, the fluctuations increase, causing the behavior to become unstable and to undergo a sudden and substantial change (e.g., abrupt performance change or injury) [40, 46]. In sum, while the control parameters induce qualitative changes in behavior, the order parameter describes such changes (Fig. 2). It means that the intricate relationship among the multiple parts of the system can be captured by the order parameters and studied.

It has been shown that in several physical and biological systems, the dynamic, captured by the proper order parameter, imposes constraints on the behavior of the parts [47, 48]. Once created, the order parameter constrains the behavior of the parts. It means that, in complex systems dynamics, the parts are enslaved by the whole (see recursive loops in Fig. 1), which is produced by the cooperative behavior of the parts [49]. Cause and effect are bidirectionally coupled. This type of circular causality has already been described in sports injuries when discussing the relationship between training load, physical capabilities, and injury risk [50]. To solve the circular causality problem, we should first realize that the order parameters allow the description of the system's evolving states. Thus, instead of investigating the individual contribution of a given number of elements of a complex system, the collective behavior can be tracked using one or a few order parameters. For example, Pol et al. [14] suggested that movement coordinative variables could be tracked to inform the approaching of the emergence of

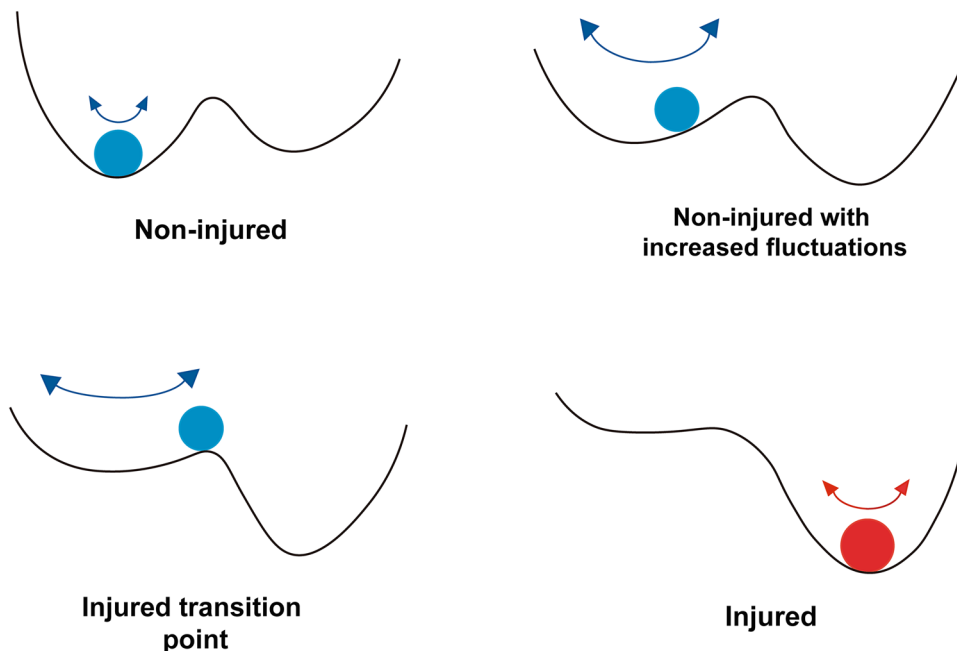
sports injury. Here, the complicatedness seen at a lower level of analysis renders simplicity at a higher level. By investigating the temporal evolution of the system, not only are the proper order parameters revealed, but also one can forecast its future evolving states.

3.1 The Role of Order Parameters' Fluctuations in Signaling Injury or Adaptation

When a given phenomenon is characterized as complex, its evolution is best represented by periods of continuity (stability) interrupted by qualitative changes in the order parameter. Near the transition points, the system's behavior becomes unstable before a new behavior emerges [21, 37]. An essential feature of complex systems is that the order parameters increase their fluctuations, close to these instability points. It means that before changing its state, the order parameter shows increased fluctuations and critical slowing down (longer times to respond to perturbations and return to its state, Table 1), hinting at the upcoming changes [51, 42, 46]. Therefore, the mapping of the order parameter's fluctuations may signal when the system is close to moving from one state to another, allowing the forecasting of its future states. In sports, this new emergent state may represent sharp improvements in performance in response to training/competition or the occurrence of injury (Fig. 2).

Several examples of phase transitions captured by order parameters have been offered in chemical, physical, and biological/social systems [40, 21, 42, 30]. In biological systems, the typical example of qualitative changes in movement organization of individuals is the occurrence of spontaneous transition in finger coordination pattern (order parameter)

Fig. 2 Injury as a phase transition preceded by increased fluctuations. The ball represents the order parameter, whose behavior is affected by a change in the global landscape (which represents the actual state of the system). The changing landscape induces larger fluctuations (bidirectional arrows) in the order parameter, whose behavior can signal upcoming injury



in response to continuing changes in movement frequency (control parameter) captured by the Haken, Kelso and Bunz (HKB) model [51]. This model allows the identification of the principles that underlay the transitions from one stable coordinative pattern to another. During the so-called phase transition experiments, when a required movement pattern (e.g., move body segments in opposite directions) becomes unstable due to an increase in movement frequency, participants suddenly change their behavior to a more stable pattern (e.g., move segments in the same direction) without any prescription or intended action. It means that the movement self-organized and spontaneously changed to a new organization that preserved the system's stability. This classical biological example characterizes the relationship between the order parameter (e.g., the relative phase between segments), the control parameter (e.g., movement frequency), fluctuations (increased relative phase variability), and self-organization (spontaneous change in movement pattern) (Table 1). Many studies applied the phase transition principles in sports [52, 53]. However, only a few have suggested these principles as a viable approach to study the process of sports injuries [14, 17].

A significant difference between the coordination phase transition experiments and the sports injury process is that we may never know the control parameters that move the system among its states [54]. In this case, one of the sports scientist's tasks should be to seek for the proper order parameter that captures the athlete's performance and track its time evolution as a result of training and competitions. Once the system's dynamics are revealed, the presence of increased fluctuations and the accompanying critical slowing down in the order parameter may indicate that the system is on the verge of a phase transition, and an upcoming injury

becomes a possible reality (Fig. 2). According to this view, a sports injury cannot be fully understood based solely on the knowledge of the parts (i.e., risk factors) in a given period. It means that we need to modify the procedures of data collection and analysis. Developments in wearable technologies and continuous activity monitoring are gaining significant momentum in sports biomechanics [55]. These developments will make collecting longitudinal data more and more possible and reliable, and these advances in technology have allowed individual endurance athletes, sports teams, and physicians to monitor functional movements to maximize performance and minimize injury [56].

4 How to Design a Complex Systems Approach to Sports Injury Forecasting

Identifying the elements of the system and defining relevant and non-linear interactions among them have been the target of the majority of the studies applying complexity concepts to sports injury etiology [9, 11, 12, 13, 57, 58, 15]. Approaches compatible with a complex system thinking, such as agent-based and system dynamics modeling, machine learning (e.g., classification trees), and neural networks techniques, are quite useful in the context of injury prevention, as they may reveal or test variables that can be changed, to diminish the susceptibility of the individual to injury occurrence [9, 12]. However, they may not be sufficient in the context of injury forecasting. To establish a synergetic or phase-transition approach to sports injury forecasting, distinct steps are necessary (Fig. 3). First, the phenomenon to be investigated must occur over a longer time scale, since increased fluctuations occurring over short

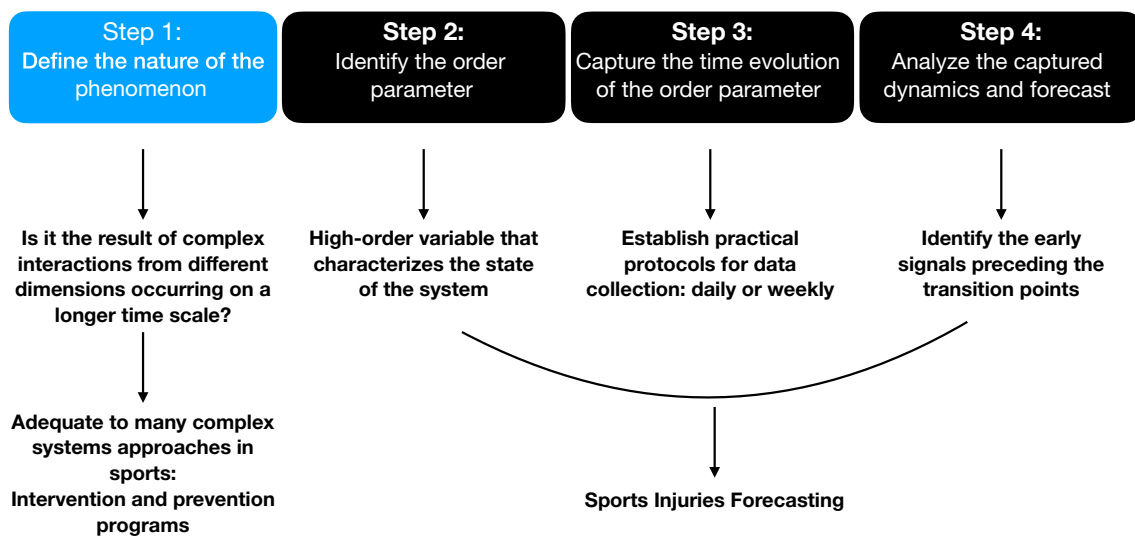


Fig. 3 Steps to establish a complex systems approach to sports injury forecasting

time scales (e.g., fast changes in the athlete's health status) may not be useful for forecasting. Second, the order parameters that characterize the system must be identified. Third, research protocols to capture the order parameters' time evolution must be formulated. Finally, methods to analyze the captured dynamics of the order parameter must be established to allow the forecasting of its future states. Below, each of these steps will be addressed accordingly.

4.1 Define the Time Scale of the Investigated Complex Phenomenon

The first step for applying a complex systems' forecasting approach is to identify the nature of the phenomenon we are investigating. Although most sports injuries, if not all, are complex phenomena [9], we need to verify if the time scale of the investigated sports injury is appropriate for a forecasting approach. For example, some contact injuries, deriving from high energy impacts, may not be properly forecasted by a phase-transition method due to their short time scale of occurrence. On the other hand, multifactorial injuries (e.g., overuse injuries, muscle strain) may be captured appropriately by phase-transition approaches. After establishing the appropriate phenomenon to investigate, the next task is to identify the order parameters, which capture the collective contribution of system's constituents. This step is the most challenging and essential for establishing a complex systems approach to sports injury forecasting.

4.2 Define the Order Parameters that Characterize the State of the System

The high-order variables that can capture the state of the system under an analysis based on synergetics are the so-called order parameters [40]. Once identified, they must be subjected to observation and quantification as they represent the collective behavior of relevant elements that constitute the system. The order parameters, either as a single (e.g., heart rate variability) or relational variable (e.g., variable related to capacity/demand relationship), represent the overall state of the system and should capture the contribution of the elements and interactions that characterize a complex system, even if they are not fully known or measurable. Thus, these high-order variables carry information about the relevant interacting parts of the system. Examples of high-order variables that can monitor different aspects of sports performance are available in the sports literature and will be addressed below. However, we should warn that their suitability as potential order parameters has not been investigated and remain only as examples of high-order variables related to physical performance that still require more investigation on their capability of signaling upcoming injuries.

One of the most successful high-order variables related to human performance is heart rate variability (HRV), which represents the fluctuations in the heart cycle interval over time and is considered to be a relevant marker of cardiac modulation [59]. As a measure of the behavior of the cardiac and autonomic nervous systems, HRV has been suggested as a marker of dynamic and cumulative loads [60, 61], of mental load [62], cumulative wear and tear [63] and to be responsive to acute stress [64]. The dynamical behavior of this global variable is affected by the demands of the cardiac musculature in response to exercise, the anatomical geometry and cardiovascular function of the heart, and adjustments that happen in different systems that are related to all aspects of cardiac and peripheral vascular control [65]. Again, even without knowing all "parts" related to HRV behavior, it indexes the contribution of many factors of the cardiovascular function. While a given value of HRV does not tell us much about cardiovascular system function, changes in HRV behavior over time may act as the signature of such function. At this moment, only an indirect relationship between HRV and injury has been reported [66]. Therefore, this variable can be seen only as an example of an order parameter to capture the dynamics of the cardiovascular system and not as an order parameter for injury forecasting.

Another variable with the potential to index the behavior of many other sports performance components is the so-called perception of effort (PE) or perceived exertion. This variable was defined by Noble and Robertson [67] as "the subjective intensity of effort, strain, discomfort, and fatigue that is experienced during physical exercise." As a global variable that captures physiological aspects of performance (e.g., physical fatigue [68]) and psychological (e.g., mental fatigue [69]), PE has been used to control and monitor internal training load [70]. Also, PE has been used as an order parameter to index physical performance, and its fluctuations and other features such as hysteresis have been studied during exercising [71–73]. Although the adequacy of PE to index sports performance has been well documented and a related measure, subjective well-being, has been reported to be linked to increased injury risk [74], its relationship to injury remains to be further explored. To be used as order parameters, PE or subjective well-being must demonstrate that, during their time evolution, erratic fluctuations are associated with qualitative changes in performance or the emergence of injury. However, it must be pointed out that, although these variables can capture factors related to physiological and psychological components, they do not bring much information about essential factors related to human movement.

Despite the adequacy of HRV and PE as high-order variables that may capture aspects related to sports performance, order parameter candidates for sports injury forecasting with a more intimate relationship with the human movement must

still be sought. If we accept that the relationship between capacity and demand is at the core of sports injury occurrence [75], it is natural to assume that this relationship could be revealed by the movement patterns involved in sports performance. Examples of order parameters associated with movement pattern transitions have been well documented, such as the earlier mentioned transition in manual movements [51] and the transition in human gait between walking and running [76]. These studies investigating movement pattern transitions as a result of instabilities in human behavior have identified the relative phase between the angular displacement of specific joints as the order parameter. In addition, the relative phase has been used to assess differences in coordination patterns and variability of these patterns in pathological gait (Parkinson's disease [77]), orthopedic injuries [78], and low back pain [79]. Although relative phase seems to be a suitable global variable to inform on upcoming changes in coordinative patterns, it is still necessary to evaluate its adequacy to capture the dynamics related to sports performance or injury.

Another approach to finding order parameter candidates at the movement level is to examine the global structure of the movement itself. Recently, several non-linear techniques have been proposed to uncover the structure of a given movement time series [80]. These time series are obtained from behavioral or physiological variables that may act as order parameters, as described earlier. The primary goal of non-linear analyses is to detect hidden determinism (chaos) in seemingly random data. Like many biological processes, the movement is a phenomenon that is sustained by physiological, neural, and mechanical processes that occur in many spatial-temporal scales. The interactions among these processes and with the ever-changing environment impose a given structure in the observed movement. This structure carries, therefore, the physiological complexity of the emerging movement pattern. For example, human locomotion is an inherently complex activity that requires the coordination and control of neurophysiological and biomechanical degrees of freedom across various spatiotemporal scales, and this complexity can be assessed through fractal analysis (e.g., detrended fluctuation analysis [81]) or entropy analysis [82]. These promising techniques have been successful in revealing differences between healthy and diseased states, as well as between situations with distinct task demands relative to the individual's capacity [83, 84]. They are frequently thought to be informative about the complex interactions between neural, physiological, and mechanical aspects of human movement [82]. Although complexity analysis of movement time series has become popular in recent years (and used to assess the consequences of sports practice [85]), its output has not been associated as an order parameter that could act as a signature of the state of the systems related to sports performance or injury occurrence.

As a system's signature, the structure of these movement time series could be tracked over time to establish the system state dynamics and reveal periods of continuity and hint at an upcoming phase transition. These measures are strong order parameter candidates for capturing the time evolution of the athletes' dynamics in response to continuing training and competitions. However, proper research protocols are needed to investigate the feasibility of order parameter candidates to capture the relationship between the athletes' capacity and the demands imposed by sports performance.

4.3 Establish Protocols to Capture the Time Evolution of the Order Parameter(s) With a Resolution Appropriate to Describe the Dynamics of the System

One fundamental aspect of complexity analysis is that any behavior can only be studied by means of its time evolution [80]. Single assessments applied during the season or pre-season, cannot reveal the dynamics of the state of the system, and therefore, they cannot efficiently inform on the possibility of upcoming events. As established previously, data from pre-season, mid-season, and post-season assessments cannot provide information about the system's time evolution and are not compatible with a complex systems approach. It does not mean that these assessments are useless. It means that they cannot be used to forecast upcoming events accurately and should not be used for this purpose.

If one wishes to apply a non-linear phase transition approach to sports injuries, new protocols of assessments must be established to capture the dynamic behavior of the high-order variables, i.e., the order parameters. Assessments must be performed according to the proper time scale necessary to reveal the phenomenon. Depending on the nature of the order parameter investigated, measurements should be done several times a day (finer resolution) or could even be performed weekly (coarser resolution). The time interval of the data should be shorter than the time scale of the critical transition of interest [86]. It is crucial to notice that the only means to study the injury process is by establishing a data time series that can capture the nature of the behavior of interest. In sports, time availability to perform assessments in athletes is frequently a limiting factor for applying measurements in finer resolutions. However, instead of assessing many variables that inform on the parts, a complex systems approach should track only the variables that could represent the global behavior of the system (order parameter). Thus, time constraints for such an approach may not be a problem. Once the dynamics of the order parameter is captured, we should apply statistical methods to identify when the behavior starts to show increased fluctuations, which indicates an upcoming qualitative change. This process of collecting limited data but over longer periods is gaining significant

momentum in sports biomechanics through developments in wearable technologies [55], allowing researchers and clinicians to monitor performance and possible patterns that may lead to injury [56].

4.4 Select Methods to Analyze the Captured Dynamics and Forecast Future States

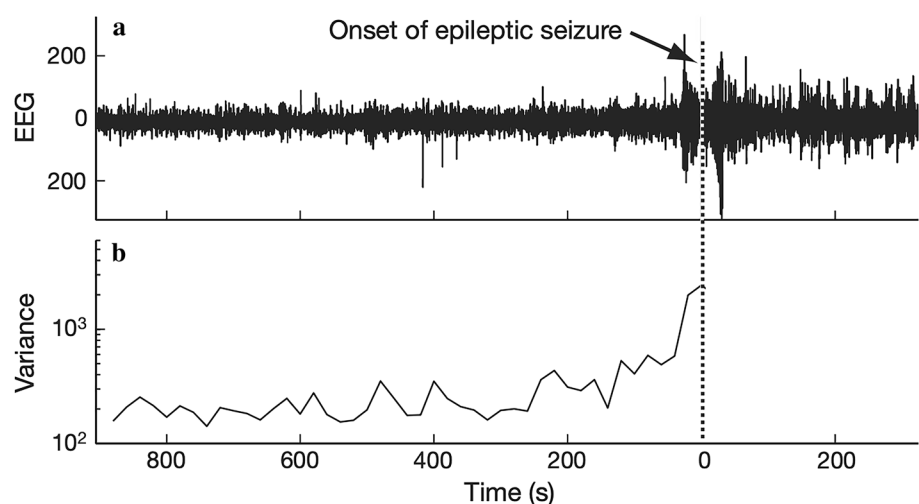
The capturing of the dynamics of the order parameter that represents the overall status of the athlete in response to training and competition is an essential step for implementing a complex systems approach. However, identifying the upcoming critical transition points and the periods preceding the transitions will require the implementation of appropriate techniques for time-series analysis. Forecasting techniques have been used in several different disciplines that deal with a complex system [87] and can be successfully applied to sports. Mapping shifts in ecological and social systems and weather and financial market forecasting are classic examples of these approaches.

One possible way of forecasting transition points (also named regime shifts) in complex systems is by identifying the changes in behavior that precede the abrupt phase transitions. These preceding changes have been named “early-warning signals” and have been consistently identified in different categories of complex systems, such as ecosystems, financial markets, and biological systems [22, 23]. Early-warning signals seem to be generic as they do not depend on the details of the analyzed system [88]. The observed behavior near the transition point is characterized by the phenomenon of critical slowing down. Critical slowing down means that, as the system approaches a critical transition, its ability to return to its stable dynamics in the face of the natural perturbations caused by the regular variations in its states or context becomes slower. This decreasing “return speed” is accompanied by an increase in the amplitude of variation

in the order parameter. This phenomenon shows that the system becomes less resilient until it reaches a *no resilience* state. Thus, at the critical point, the system loses its ability to return to the original stable state (e.g., non-injured state) and assumes the new stable state (e.g., injured state). Critical slowing down can be identified by measures that capture the increased amplitude variation of the observed behavior. As in many physical, chemical, and biological systems, the standard deviation of the order parameter may show identifiable increases before the critical point (Fig. 2). For example, McSharry et al. [89] have shown that the onset of an epileptic seizure (as a phase transition) can be signaled in advance by means of an increase in the electroencephalography activity variance (Fig. 4). Another measure used to identify the transition point is the autocorrelation (of low time lags) of the order parameter, which increases as the critical point approaches [90]. For example, an autocorrelation of lag-1 (the correlation of the order parameter value in one time with its value in the preceding time) will increase, since with more substantial variations, subsequent values of the order parameter tend to vary in the same direction (i.e., they escape from the stable state for a longer time and then take a longer time to return). In addition, other measures may act as early signals pointing at the transition point, such as skewness and flickering (see comprehensive reviews in Scheffer et al. [22] and Scheffer et al. [23]). Although theoretical and methodological cautions should be taken [22, 86], this approach may be promising for anticipating injury. Whether the same kinds of early-warning signals occur in the athlete’s behavior in the vicinity of an injury and how these early signals are useful for injury forecasting should be one of the focusses of future investigations on sports injury.

In addition to classical approaches to investigate increased variability close to the transition points, more refined non-linear time-series analysis techniques may also prove to be of great value in injury forecasting. Recently,

Fig. 4 Abrupt phase transition in brain activity before the onset of an epileptic seizure, showing the activity variance as an early-warning signal. **a** Electroencephalography (EEG). **b** Variance of the EEG showing a visible increase before the seizure onset (vertical line) Reproduced from McSharry et al. [89], with permission



the treatment of financial markets as paradigmatic examples of complex systems [91] led researchers to the application of network theory quantifiers to tackle the issue of forecasting future events [92]. In the sports literature, the use of network science is already a reality [93, 94]. This novel approach to the analysis of the dynamics of complex systems improves the understanding of the underlying mechanisms driving the emergence of instability periods [95] and gives new perspectives to follow up and better manage unexpected events [96]. A recently explored method in complex networks is the visibility graph algorithm [97], a method that considers the visibility of elements in a time series to construct a network. According to Zhang and Small [98], chaotic dynamical systems have a corresponding complex network topological signature. This topological signature may reveal the state of the system and signals the possibility of upcoming events.

Uncovering the global behavior of a dynamic system requires knowledge about the conditions in which the phenomenon studied emerges. In sports, it may be challenging to identify if a given change in the order parameter behavior is related to a change in performance (increase or decrease) or even if an imminent injury may occur. In addition, since any training is aimed at modifying the athlete, some fluctuations in behavior could only reflect these changes and may be thought of as desirable or needed. Therefore, in some cases, the sports scientist must be able to parse out the nature of fluctuations. It is possible to assume that in a group of athletes submitted to a similar working load, common fluctuations demonstrated by the order parameter will reflect these desired changes. Analysis that removes these common fluctuations may help to reveal changes in individual behaviors that do not follow the expected group effects of training. Detrending methods [99] may help to parse out the effects of training from possible maladaptation that could be related to the increased possibility of injury. After removing extraneous sources of fluctuations, the sports scientist should select the proper analysis to capture the dynamics of the time evolution of the athlete's behavior.

Understanding the complex nature of sports injury allows the selection of the appropriate tool to reveal the phenomenon. If the previously addressed steps (Fig. 3) are appropriately established, the methods used to analyze the captured dynamics and to forecast future events will be complementary to how the information about the nature of the behavior was collected. If we understand that sports injuries emerge from non-linear and complex interactions, the analysis of the time series markers that adequately capture this phenomenon could be done by means of different methods. Only then will we be able to implement a full complex systems approach to sports injury forecasting.

5 Conclusion

The characterization of the elements and interactions that constitute the system has been the target of the majority of the studies applying complexity to sports injuries. Although fundamental, this characterization does not encompass the full reasoning defined by a complex system thinking and has a low potential for injury forecasting. A synergetic, phase-transition, approach may be an adequate procedure for sports injury forecasting. Embracing complexity in sports is to philosophically accept that the injury occurrence cannot be predicted solely based on the variables (risk factors) we have been exploring so far, as the intricate non-linear relationships among many factors and constraints acting on a complex system and the ever-present context variability may render classical predictions useless. To apply complexity to sports injury forecasting is to assume that interactions among the elements of the system are mostly unknown. However, this mostly unknown behavior at the elements' level can produce ordered behavior on the macroscopic level, which can be captured by an order parameter. Thus, injury forecasting requires the identification of the proper order parameter and the capturing of its time evolution. By establishing this methodological sequence, we will be able to implement techniques to identify the changes that signal an upcoming transition in athletes' behavior. These changes may reflect the current state of the athlete that may lead to an upcoming injury, allowing sport professionals to implement actions to prevent or mitigate the effects of sports injuries. A phase transition approach provides additional forms to examine the emergent phenomenon of injury (multi)causation, changing the traditional experimental paradigm in sports injury research.

Compliance with Ethical Standards

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