An Ecological Dynamics Approach to ACL Injury Risk Research: A Current Opinion

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Abstract

Research of non-contact anterior cruciate ligament (ACL) injury risk aims to identify modifiable risk factors that are linked to the mechanisms of injury. Information from these studies is then used in the development of injury prevention programmes. However, ACL injury risk research often leans towards methods with three limitations: 1) a poor preservation of the athlete-environment relationship that limits the generalisability of results, 2) the use of a strictly biomechanical approach to injury causation that is incomplete for the description of injury mechanisms, 3) and a reductionist analysis that neglects profound information regarding human movement. This current opinion proposes three principles from an ecological dynamics perspective that address these limitations. First, it is argued that, to improve the generalisability of findings, research requires a well-preserved athlete-environment relationship. Second, the merit of including behaviour and the playing situation in the model of injury causation is presented. Third, this paper advocates that research benefits from conducting non-reductionist analysis (i.e. more holistic) that provides profound information regarding human movement. Together, these principles facilitate an ecological dynamics approach to injury risk research that helps to expand our understanding of injury mechanisms and thus contributes to the development of preventative measures.

Keywords: Ecological Dynamics, ACL, Injury risk research, Non-reductionist, Self-organisation

1 Introduction

Non-contact anterior cruciate ligament (ACL) ruptures are injuries that typically occur during dynamic movements such as rapid deceleration or change of direction [1]. These injuries involve significant financial costs for society, large personal burden due to the great number of days of absence from training and match play [2, 3], and a high risk of post-traumatic osteoarthritis [4]. Due to these long-lasting consequences, the prevention of ACL injuries should have top priority [5]. Over the past 20 years, researchers have identified modifiable (biomechanical and neuromuscular) risk factors related to the mechanisms of ACL injury in team sports [e.g. 6–9]. These risk factors have provided information for the development of ACL injury prevention measures [5], through the 'Sequence of Prevention' model [10]: i.e., 1) establishing the extent of the sports injury problem (incidence & severity), 2) establishing aetiology and mechanism of injuries, 3) introducing preventive measures, and 4) assessing their effectiveness by repeating step 1.

Establishing the modifiable risk factors and mechanisms of injury through injury risk research is an essential step in the 'Sequence of Prevention'[10]. These lab-based studies typically aim to mimic movements in that characterize injury risk scenarios such as change-of-directions or jump landings and assess the biomechanics associated with these movement tasks [11]. Considering the importance of these injury risk studies, we have the following concerns regarding their methods. First, injury risk research typically takes place in a laboratory setting that fails to preserve the athlete-environment relationship. As a result, the generalisability of findings may be limited. Second, injury risk research is often conducted from a strictly biomechanical approach. This is representative of adopting a 'narrow' model of injury causation, as this approach may overlook the effects of other variables, such as player behaviour or the surrounding environment. Third, injury risk studies that analyse single-joint biomechanics using linear statistical measures are reductionist and neglect information about the adaptability and complexity of human movement. Together, these aspects of injury risk research methods limit the knowledge gained from these studies and thus narrow our understanding of injury risk (Figure 1A).

To address these limitations, we propose an approach from an 'ecological dynamics' perspective that considers the human body as a complex adaptive system that interacts with its environment, which is best studied at the athlete-environment level of analysis [12]. Although this ecological dynamics perspective is already prominent in the fields of sports performance [13–15] and sport psychology [12, 16, 17], its implementation in injury risk research is limited. While this paper specifically discusses non-contact ACL injury risk research, this approach is also applicable to other domains. This article consists of three parts. First, we describe how movements emerge through self-organisation and underline the importance of 'context' in studying movement behaviour and its relation to injury situations. Second, we discuss three principles that enhance ACL injury risk research (Figure 1B): preserving the athlete-environment relationship, including behaviour and the playing situation in the injury causation model, and conducting non-reductionist (i.e. more holistic) analysis. Finally, we conclude with an example of a study design that adheres to the proposed principles. By providing these principles, we hope to offer researchers an approach that helps expand the understanding of injury mechanisms and thus contributes to the development of effective preventive measures.

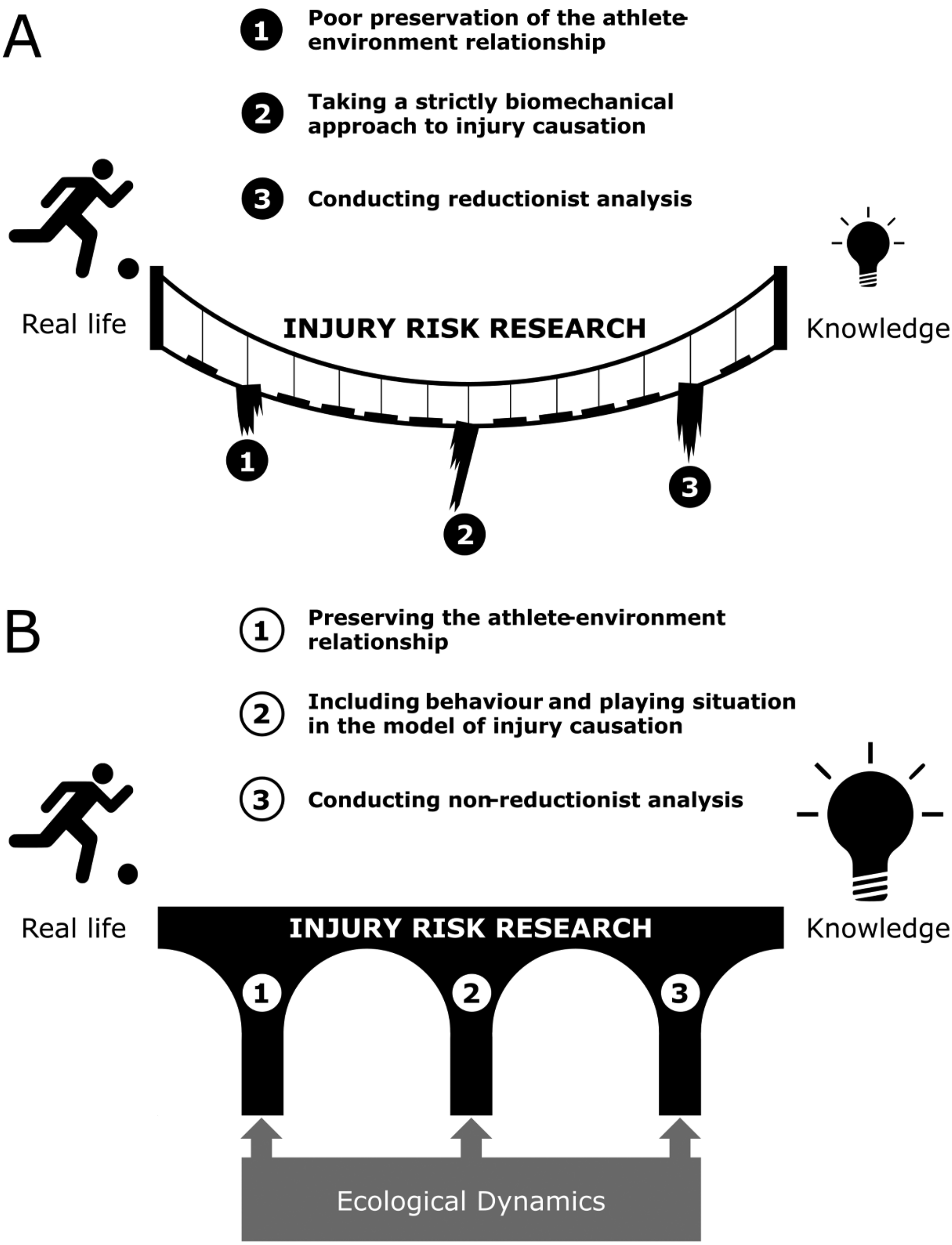

Figure 1. Schematic representation of injury risk research as the bridge between *real life* and *knowledge*. A) Limitations of current injury risk research methods are pitfalls that limit the knowledge obtained from these studies. B) Principles for an ecological dynamics approach to injury risk research. These principles provide a foundation for research that is more generalizable and less reductionist, expanding the knowledge that is obtained.

2 'Context' and self-organised movements

Human movement can be viewed as the emergent result of the interaction between the athlete and its surrounding context [18]. The athlete performs in a context that is shaped by three types of constraints; the individual constraints, the environmental constraints, and the task constraints (Figure 2). Individual-related constraints, for example, may concern the athlete's characteristics such as height, weight, limb length, fatigue, or anxiety [19]. Environmental constraints may include features like the type of terrain, light condition, weather, or boundaries of the field. Task constraints may include the goal of the task and any rules or objects that specify or constrain the athlete's response dynamics, for instance the actions of other players [19]. Together, these constraints shape the context in which the athlete perceives and acts. Movement in sport is therefore not produced by an isolated athlete, but emerges from a dynamically varying coupling between the athlete's characteristics, the stimulus-rich environment, and the desired actions (i.e. tasks) [20].

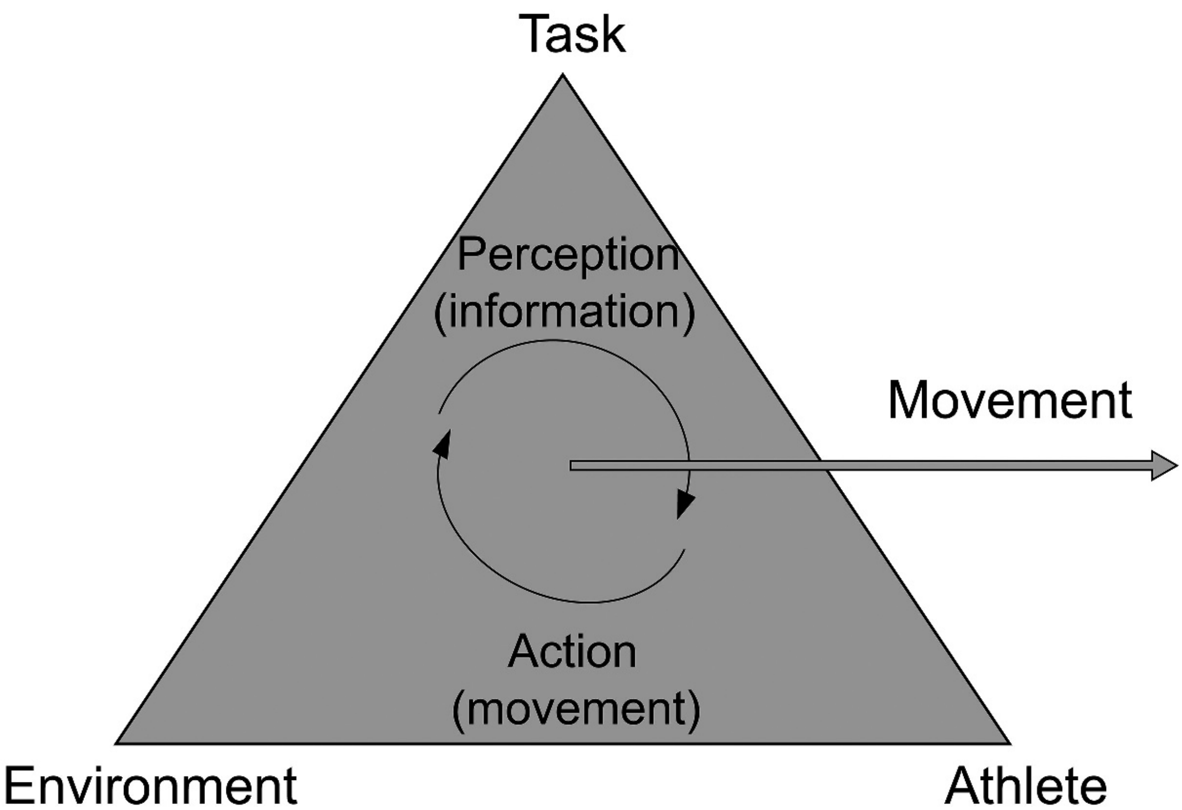

Figure 2. Movement is the emergent result of the athlete perceiving and acting within a context that is shaped by its constraints [18]. An adapted figure from Davids et al. [21].

Adopting this view of movement behaviour has two important consequences for studying movement. First, most constraints are changeable and in fact may change rapidly (e.g. the relative position of players, fatigue levels, ball possession). Second, the relationship between the produced movement and the underlying constraints is nonlinear. To clarify, small changes to individual, task or environmental constraints can cause dramatic changes in movement patterns [19]. Additionally, changes in different types of constraints can result in the exact same effect on the movement pattern [22]. Recognising the changeable nature of constraints and the nonlinear relationship between constraints and movement is essential in studying movement behaviour.

In the process of self-organised movements, perception and action are coupled and cannot be studied in isolation. Expert athletes are not solely proficient movers, but excel in perceiving information from the environment and execute actions accordingly [16, 23, 24]. This direct connection between movement and the environment warrants research at the athlete-environment level. Therefore, if experimental studies intend to investigate game-like movement behaviour of athletes, aiming to preserve the athlete-environment coupling by adding game-specific stimuli is essential to elicit generalizable movement patterns [25].

3 Principles for an ecological dynamics approach

3.1 Preserving the athlete-environment relationship

Athletes in team sports have to quickly perceive not only their own action opportunities but also those of opponents and teammates, while performing a movement. These continuous actions are performed under time pressure as movement possibilities emerge and disappear. A non-contact injury is therefore the result of a series of self-organised movements that emerge from the interaction with quickly changing constraints. Video analysis has shown that non-contact ACL injuries in team sports typically occur when the athlete is in close proximity to an opponent, while the athlete or the opponent is in possession of the ball [26–28]. To acquire generalizable information about risk factors and injury mechanisms in these scenarios, experimental research should strive to present athletes with game-like variables so that the elicited movement is more reflective of the movements in injury scenarios.

Traditionally, the laboratory-based injury risk studies inherently provide athletes with limited room for self-organisation of their movements. Athletes are usually instructed to move along a predefined trajectory at a certain speed or to perform a jump in a marked area. Generally, game-like variables, such as interactions between participants or between the athletes and a ball, are omitted to preserve the standardisation and the repeatability of the protocol. Instead, participants are often instructed to respond to a simple visual cue that is atypical of the complex visual stimuli in game situations (e.g. an LED lighting up or an arrow being displayed) [29]. Furthermore, trials wherein the participant fails to successfully complete the prescribed task are typically discarded. As a consequence, the movement tasks studied in the lab are different from the movement behaviour that would emerge from scenarios on the pitch [25]. The poor generalisability of these studies limits a critical step of the 'Sequence of Prevention' model; to identify risk factors and injury mechanisms[10].

In the last decade, researchers have made efforts to include game-like variables into their experiments. For instance, some studies have included sport-specific dual-tasks like dribbling, intercepting, or passing a ball during a change-of-direction manoeuvre [30–33]. Other studies had the athlete respond to an opponent or a video projection of an opponent in a simulated game scenario [34–37]. In addition to this, rather than discarding unsuccessful trials, some studies have investigated the underlying coordination of unsuccessful task performance [38] or used the number of unsuccessful trials as a performance measure [24]. These improvements in methods are commendable and exemplary steps towards the first principle: preserving the athlete-environment relationship. However, researchers should remain careful when generalising findings from these studies. Studies should first specify the context toward which they intend to generalise their findings, and then explain how that context is represented in their experimental designs [39].

Researchers that wish to adhere to this principle should consider designing experiments which maintain the athlete-environment coupling by including elements of the sport that are relevant to the game scenario of interest; such as the ball, other players, and objectives that are related to real game scenarios (e.g. evading, intercepting). Of course, such experiments are best performed on the field. Developments in wearable inertial sensor technology are now facilitating performance evaluation on the field rather than in the laboratory [40]. Nevertheless, when investigating dynamic movements (e.g. jumping), the validity of lower extremity joint kinematics in the frontal and transverse planes is currently only deemed 'fair-to-good' (i.e. on a scale of 'poor; 'fair-to-good'; 'excellent') and thus warrants further developments [41].

Efforts to improve the athlete-environment relationship will likely increase complexity of the dataset due to an increase in the number of uncontrolled variables. Researchers are therefore challenged with finding the balance between the preservation of the athlete-environment coupling and the interpretation of the dataset. For instance, navigating around training dummies introduces more coordinative complexity when compared to preplanned sidestep cutting. Likewise, replacing training dummies with real opponents adds additional coordinative complexity, as well as variables related to affordance perception [16]. We advise to take small steps on this spectrum of athlete-environment preservation, so that it aids the interpretation of the increasingly complex datasets.

3.2 Including behaviour and the playing situation in the injury causation model

It has long been popular to study ACL injury risk using a biomechanical approach [42, 43]. A goal of this approach is to identify modifiable risk factors that can provide information for prevention strategies [5]. The focus typically lies on describing biomechanical characteristics at a specific foot contact during a change-of-direction or landing from a jumping movement [44, 45]. The movement tasks that are investigated are designed to mimic the movements during which ACL injuries occur. This approach is appropriate for research regarding the internal and external joint loads of such movement tasks, and it may serve as a 'stepping stone' to facilitate the interpretation of more complex models. However, this approach is incomplete for a comprehensive understanding of actual injury mechanisms[46].

ACL injury risk research demands an approach that is based on a more comprehensive injury causation model. In 2005, Bahr and Krosshaug [47] proposed a conceptual model describing the factors that contribute to the inciting event of an injury. According to this model, the description of an inciting event should not only include information about the biomechanical characteristics, but also about the playing situation and the behaviour of the athlete and other players. Descriptive video analyses have shown that athlete behaviour and playing situations are highly sport-specific [48, 49]. This highlights the importance of athlete behaviour and playing situations in the inciting event of injury and thus supports the inclusion of these factors in the injury causation model that researchers adopt.

To determine the effects of player behaviour and playing situations on injury risk, we suggest designing experiments that preserve the athlete-environment relationship while considering factors such as perceptual skills and decision making of the athletes (e.g [50]) For instance, by studying the visual exploratory behaviour of athletes, it might be possible to link visual exploratory behaviour prior to an action with the biomechanical characteristics during the action [51]. Taken together, adopting this comprehensive injury causation model likely expands our understanding of injury risk and thus may inform new prevention strategies.

3.3 Comprehensive movement analysis requires non-reductionist methods

A movement pattern is a series of movements over time. The reduction of this time series during analysis needs to retain the information of interest regarding the research questions. In injury risk studies, researchers typically analyse the kinematics of movements using linear descriptives such as means, ranges and standard deviations. The results are often joint-specific snapshots of the mechanical properties during short time windows, e.g. peak knee valgus moment during weight acceptance [11]. Researchers then compare the kinematics or kinetics to examine differences between groups, interventions, conditions, or exercises. In this section, we will describe how this 'reductionist analysis' often reduces the data to such an extent that it discards important information regarding injury risk. We then discuss how the use of linear descriptives overlooks relevant information and propose a few non-reductionist (i.e. more holistic) methods that provide profound information that helps our understanding of injury risk mechanisms.

The reduction of a series of movements to a short time window neglects information regarding preceding movement behaviour. By doing so, information regarding movement strategies that constitute safe biomechanical characteristics is neglected. Alternatively, safe biomechanics may have involved unsafe preceding movement behaviour. For example, the penultimate step of a change-of-direction has shown to provide important information for the description of the movement behaviour prior to an injury [52]. Including the previous steps into the window of analysis provides information regarding movement strategies that facilitate the biomechanics at final contact. By expanding the measurement window, the information that constitutes the variable of interest is retained. This allows for the extraction of information regarding safe movement strategies which is essential for informing prevention programmes. An example of a linear analysis method that is appropriate for analysing time series is statistical parametric mapping (SPM) [53].

Experimental studies usually collect their data through multiple trials of a movement task. As movement patterns differ between trials [54], within-person movement variability is ever present in the data. The kinematic study of movements therefore inevitably involves movement variability. Traditionally, variability is considered noise and quantified as the deviation from the mean [54]. There are a few important limitations in the analysis of movement variability using linear descriptives. First, the use of linear descriptives assumes that lower variability equals a more stable system with less noise. However, there are examples where movements with high variability are more deterministic (i.e. predictable variability), which shows greater stability in a movement [54, 55]. Variability therefore requires a measure other than the standard deviation to describe the stability of movement patterns. Second, linear descriptives reduce a time series to a single description, discarding any information regarding the temporal structure of variability [54]. Third, the comparison of effects between groups can be inaccurate, as within-person variability may be higher than between-group variability [56, 57]. Fourth, when assessing the effect of a constraint on a movement task, the effect can differ between individuals, which violates the assumption of homogeneity of linear testing models [57].

Human movement is inherently variable and this plays a vital role in the adaptability and coordination of the movement system [58]. There are a few analysis methods that provide profound information that linear analysis methods do not provide. First, the uncontrolled manifold (UCM) hypothesis relates variability towards a performance variable that the movement system aims to control [59]; variability is divided into variability that affects the performance variable and variability that does not. This way, UCM-based analysis does not solely quantify variability, but offers the possibility to relate it to a performance measure of movement [59]. Second, the Lyapunov exponent gives a description of the stability of the system in repeating movements, offering the possibility to measure stability in a variable movement pattern [54]. For example, a decrease in functional responsiveness (i.e. the response to a perturbation) has been shown in the ACL-deficient knee of athletes using Lyapunov exponents [60]. Third, entropy analysis methods such as the approximate [61], multiscale [62], or sample entropy [63], allow for the description of the rigidness of the system [54, 64]. By comparing the rigidness of a system between conditions, the effect of the condition can be described while within-movement variability is not neglected. For example, increased variability has been revealed in the acceleration of rugby players in a ball situation compared to a no-ball situation [62].

The use of non-reductionist analysis methods such as the UCM, Lyapunov exponent, and entropy analysis provides profound information regarding the coordination of the motor system and its response dynamics that linear measures do not provide. For example, approximate entropy analysis found significant differences in postural control between previously concussed participants and healthy controls, while the initial analysis using linear statistics deemed participants to be recovered of their concussion [61]. However, despite their value, there are limitations to the use of these methods. For instance, the sample entropy analysis of biomechanics in cyclical movements is sensitive to changes in the trajectory of the movement [63]. Likewise, the calculation of the Lyapunov exponent requires repeated movements within a trial. To add, most non-reductionist methods require a larger sample size to correctly analyse variability (e.g. [65, 66]). Nevertheless, expanding the toolkit used in injury risk research with non-reductionist methods in appropriate situations will allow researchers to extract information which linear measures otherwise neglect. As a result, it will improve the understanding of the relationship between the coordination of the motor system, the role of movement variability, constraints and injury risk.

4 A study design that adheres to these three principles

To exemplify the use of these principles, let us imagine a study that aims to examine the effect of fatigue on the kinematics of sidestep cutting in a ball vs. no ball condition, aimed towards football research. The *athlete-environment coupling* would be preserved by capturing kinematic data on the football pitch using inertial sensors. Participants would perform sidestep cuts around training-dummies, allowing for the movement to self-organise closer to how it would in real matches. The real-world constraints would be mimicked by inducing sport specific fatigue through a football match simulation [67]. The study would *include behaviour and the playing situation to the injury causation model* by investigating a potential confounding or mediating effect of visual exploratory behaviour by testing conditions with and without ball possession. Furthermore, the study would comply with the principle of *non-reductionist analysis* by complementing linear descriptives with an UCM analysis. Using the UCM analysis, changes in the variability of joint-angles can be related to a control strategy such as the stability of the centre of mass of the athlete [68]. This analysis may identify mechanisms between fatigue and unstable movements. Such mechanisms may lead to the identification of novel risk factors, which can then be used to identify players that are at increased risk of fatigue-induced injury. The results of the study would be discussed in the context of the experiment and related to the context of the performance environment [14]. As changes in behaviour are non-linearly related to movements (see section 2), an explicit description of the context of the experiment would be required, allowing for a better comparison of effects between studies and providing suggestions for future research.

5 Conclusion

This paper presents an ecological dynamics approach to injury risk research through three principles. It is important to realise that the implementation of only one of these three principles will not yield the desired effect. For example, maintaining the athlete-environment coupling whilst using only linear measures will still neglect relevant information. Using non-reductionist (i.e. more holistic) methods in a non-representative lab setting does not provide profound information regarding the performance context, limiting the generalisability of the results. Similarly, limiting the research scope with a strictly biomechanical approach to injury causation prevents the possibility to span results across relevant fields. Thus, the implementation of this ecological dynamics approach warrants a simultaneous consideration of all three principles.

Undoubtedly, conducting research according to these theoretical principles poses practical challenges that warrants attention. Firstly, efforts to preserve the athlete-environment relationship may increase the complexity of datasets. Researchers should therefore take small steps in preserving the athlete-environment relationship in order to aid the interpretation of these increasingly complex datasets. Secondly, when including playing situations and behaviour in the injury causation model, it may help to form multidisciplinary research groups (e.g. biomechanists, sport psychologists, coaches/trainers) and learn from each other's perspectives. Thirdly, to correctly implement non-reductionist analyses, researchers should adjust their study designs so that they meet the requirements of the analysis methods (e.g. sufficient sample size, appropriate measurement window). By collaborating with statisticians, mathematicians, or other experts, researchers can explore the wealth of available methods to find appropriate analyses for their research questions. We believe that studies using this approach will be more generalizable and less reductionist. This results in improved understanding about risk factors and injury mechanisms, thereby contributing to the sequence of prevention.

Declarations

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