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CURRENT OPINION

Challenging Conventional Paradigms in Applied Sports Biomechanics Research

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Abstract

This paper evaluates the effectiveness of, and highlights issues with, conventional paradigms in applied sports biomechanics research and comments on their capacity to optimise techniques of *individual* athletes. In empirical studies, group-based analyses often mask variability between athletes and only permit probabilistic 'in general' or 'on average' statements that may not be applicable to specific athletes. In individual-based analyses, performance parameters typically exhibit a small range and a flat response over iterative performance trials, making establishing associations between performance parameters and the performance criterion problematic. In theoretical studies, computer simulation modelling putatively enables athlete-specific optimum techniques to be identified, but given each athlete's unique intrinsic dynamics, it is far from certain that these optimum techniques will be attainable, particularly under the often intense psychological pressures of competition, irrespective of the volume of practice undertaken. Sports biomechanists and coaching practitioners are advised to be more circumspect with regard to interpreting the results of applied sports biomechanics research and have greater awareness of their assumptions and limitations, as inappropriate interpretation of results may have adverse consequences for performance and injury.

Key Points

Group-based analyses often mask variability between athletes and only permit probabilistic 'in general' or 'on average' statements that may not be applicable to specific athletes.

Individual-based analyses typically exhibit a small range and a flat response over iterative performance trials, making establishing associations between performance parameters and the performance criterion problematic.

Computer simulation modelling putatively enables athlete-specific optimum techniques to be identified, but given each athlete's unique intrinsic dynamics, it is far from certain that these optimum techniques will be attainable.

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1 Introduction

The primary aims of sports biomechanics are to enhance performance and reduce injury risk [1]. To achieve these goals, the sports biomechanist, often in conjunction with the coach, will use qualitative and quantitative analysis methods to examine an athlete's technique in an attempt to identify technical deficiencies or irregularities that inhibit performance and/or cause injury, before prescribing remedial action to rectify them [2, 3]. However, owing to the amount of movement variability in the techniques of athletes operating at even the highest level of sports performance [4, 5], the task of distinguishing technical errors or faults from functional adaptations or stylistic idiosyncrasies is not straightforward. Some approaches to this problem, such as the grandiosely entitled 'coaching–biomechanics interface' [6], are predominantly driven by the coach's experiential knowledge and can lack objectivity when attempting to identify technical limitations. Other, more traditional, empirical approaches do not have this issue, but yet, they do not appear to have had a substantive impact on enhancing sports performance or reducing injury risk, despite suggestions to the contrary [7, 8]. As it is generally accepted that any biomechanical analysis and subsequent technical intervention strategy should be evidence based or, at least, research informed, the aim of this paper is to evaluate the effectiveness of, and highlight issues with, conventional paradigms in applied sports biomechanics research and comment on their capacity to optimise techniques of *individual* athletes.

2 Empirical Approaches in Applied Sports Biomechanics: Identifying Aspects of Technique Associated with Performance and Injury

Two basic empirical approaches—the 'contrast' and 'correlation' approaches [9, 10]—have traditionally been adopted in applied sports biomechanics studies. The former refers to the contrasting of mean 'performance parameter' (e.g. joint angle, segment speed) data obtained from two or more groups of athletes that are heterogeneous on some level (e.g. expertise, age, sex). The latter refers to the correlation of performance parameter data and some outcome measure or performance criterion (e.g. release speed, distance hit) in a single group of athletes that is homogeneous, usually in terms of expertise or some proxy. Of these two approaches, the correlation approach has been the most prevalent in the applied sports biomechanics literature because the aim of many studies has been to establish relationships or associations between performance parameters and a performance criterion in an attempt to make inferences about causative mechanisms underpinning performance (and, occasionally, injury) in high-performance athletes. The contrasting of high-performance athletes with their less accomplished counterparts has received less coverage because this approach can yield somewhat trivial results (e.g. experts produce larger peak body segment angular velocities, greater release/impact speeds, and more accurate outcomes than non-experts; see Glazier et al. [11]) and because the number of athletes required would need to increase at least twofold, which would be logistically burdensome, particularly given the labour-intensive nature of data reduction techniques (e.g. manual coordinate digitising) traditionally used to generate kinematic time series data.

A typical finding from applied sports biomechanics studies adopting the correlation approach is that particular performance parameters are significantly related to, or are associated with, the performance criterion (as determined by correlation coefficients that exceed the critical r value) and are, therefore, deemed to be important determinants of performance. Occasionally, the correlation approach has been extended to incorporate regression analysis to identify the performance parameters that are the best predictors of the performance criterion and their respective contributions. For example, Chu and colleagues [12] used a series of stepwise linear regression models to identify performance parameters at specific instances during the golf swing that accounted for 44–74% of the variance in the initial ball velocity. The results of this study also enabled the authors to make several somewhat tenuous predictive statements about performance parameters and performance outcomes [e.g. a 1 standard deviation (SD) increase in lead knee flexion angle at the top of the backswing resulted in a 0.203 SD increase in ball velocity]. Similarly, Worthington and colleagues [13] used stepwise linear regression to identify four performance parameters—run-up speed at back foot contact, knee angle at ball release, upper trunk flexion between front foot contact and ball release, and shoulder angle at front foot contact—that accounted for 74% of variation in ball release speed in high-performance cricket fast bowlers. These findings have subsequently been used to directly inform coaching practice [14].

An important issue with studies adopting the aforementioned group-based approaches is that they often mask variability between athletes [15] and only permit probabilistic 'in general' or 'on average' statements that may not necessarily be applicable to specific athletes [16]. As Bouffard [17] stated, "propositions about people cannot necessarily be derived from propositions about the mean of people because the patterns found by aggregating data across people do not necessarily apply to individuals" (p. 371). This seemingly rarely acknowledged, but often-made, interpretation error, termed the 'ecological fallacy' [18], has significant implications for the practical application and functional utility of applied sports biomechanics research adopting this approach. For example, taking the findings of Worthington and colleagues [13], it may be concluded that, to improve fast bowling performance, a given fast bowler should attempt to increase their run-up speed, delay the circumduction of their bowling arm, straighten their front knee, and flex their upper trunk more. Although these technical modifications may produce the desired increases in ball release speed for some bowlers, they are likely to be counterproductive or unachievable for others, and could be injurious for both owing, in part, to incompatible 'intrinsic dynamics' (see Sect. 3 for an elaboration of this concept). Furthermore, given that there are numerous elite international fast bowlers who do not exhibit some or all of these characteristics, using them in a talent identification programme, as suggested by the authors, would appear to be unwise, as future high-performance fast bowlers may be overlooked [19].

Another group-based approach that has received some, albeit very limited, coverage in the applied sports biomechanics literature involves the averaging of kinematic data across athletes to establish a criterion movement pattern or 'standard motion' that can be used for comparative purposes to identify technical faults [20, 21]. One of the seemingly few virtues of this approach is that it does, at least, provide some insight into 'technique'—defined by

Lees [3] as "the relative position and orientation of body segments as they change during the performance of a sport task" (p. 814)—which the performance parameters used in the correlation and contrast approaches typically do not (see Glazier and colleagues [11, 19, 22] for an elaboration). However, this approach does implicitly assume that all movement variability is noise or error and that, by calculating an averaged kinematic profile across athletes, this noise or error can be reduced or removed, leaving a 'common optimal movement pattern' that all athletes should aspire to achieve. Although Ae and colleagues [20, 21] claimed, without much supporting evidence, that the resulting 'standard motion' was superior to the 'elite athlete template' [23], research from the motor learning and control literatures has suggested that this 'one-size-fits-all' approach, where the criterion movement pattern is either derived from an averaged profile or based on the technique of an elite athlete, may not be an effective strategy owing, in part, to the unique organismic constraints that each individual athlete possesses [24, 25].

To identify the biomechanical factors that contribute most to individual performance, there is growing recognition of the need to adopt more individual-based analyses [26–28]. Rather than analysing a single 'best' or putatively more 'representative' average trial for each athlete, as is typically the case in group-based analyses, an individual-based approach requires performance parameters to be measured over iterative performance trials for each athlete and correlated with the respective performance outcomes of each trial. Although individual-based approaches have seldom featured in the applied sports biomechanics literature, presumably due to the reluctance of academic journals to publish case studies owing to their perceived lack of generalisability, they have been shown to produce anomalous results in comparison to group-based analyses (see Hay [29], Yeadon and Challis [30], Ball et al. [31], and Yeadon [32] for examples). However, as Yeadon [32] acknowledged, because movement patterns tend to be stable over iterative performance trials for a given set of environmental and task constraints, performance parameter data usually have a comparatively narrow range and a flat response (Fig. 1). If anything, a quadratic (i.e. inverted-U), rather than a linear, relationship will exist between many performance parameters and performance outcomes over iterative trials for a given athlete for many sports techniques. For example, if the peak angular velocity of the pelvis during the golf swing, which has been shown to be associated with club-head speed in group-based studies [33], is too high or too low, the timing of the acceleration and deceleration of subsequent body segment rotations in the kinematic chain is likely to be disrupted, leading to an inefficient proximal-to-distal transfer of energy and momentum, and lower club-head speeds.

A further complicating issue that restricts the practical application and functional utility of individual-based analyses is that the associations between performance parameter data and the performance criterion are derived from *existing* performances. In other words, this type of analysis only provides information about what the athlete is currently able to do within the constraints imposed by his or her movement system and not what he or she may be capable of doing should those constraints be removed or relaxed. From the athlete's perspective, kinematic information describing movement patterns just performed is only moderately useful in that it can be compared against movement patterns recorded from past performances and can supplement intrinsic (kinaesthetic) feedback. Arguably of greater benefit, however, is kinematic information describing his or her optimum technique, as movement patterns just performed can be objectively compared against this criterion template to identify technical limitations and prescribe remedial action to maximise performance and minimise injury risk [34]. Although it could be argued that many elite athletes are already working at, or very near to, their optimum technique having gone through a long process of self-optimisation from years of extensive (deliberate) practice [35], it is possible that this technique is only a local optimum (i.e. the

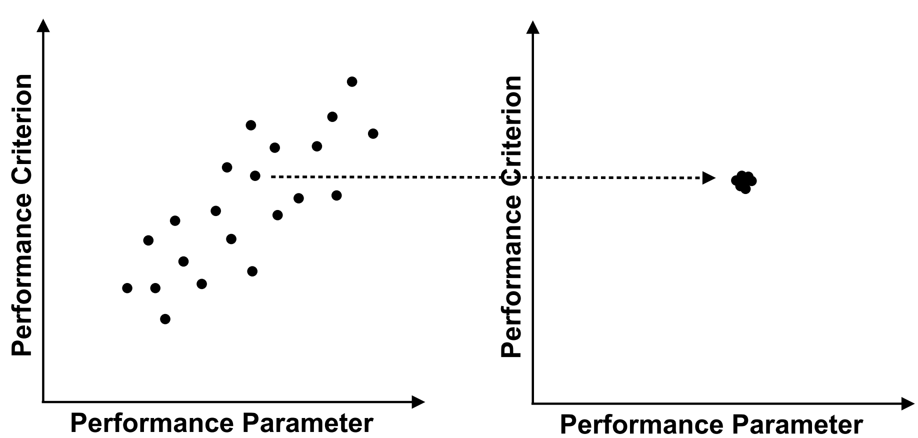

Fig. 1 Hypothetical data from 20 athletes performing 1 trial each (left) and 1 of those athletes performing 20 trials (right). The strong and reliable association between the performance criterion and the performance parameter in the group-based analysis becomes weaker and less reliable in the individual-based analysis, owing to the narrow range and the flat response of the data

best solution in a neighbouring set of possible solutions) and that a global optimum (i.e. the optimum solution among all possible solutions) is yet to be realised [36]. To ascertain whether a given athlete is capable of performing at a higher level and, if so, what technical modifications are necessary to achieve it, alternative theoretical approaches have typically been adopted.

3 Theoretical Approaches in Applied Sports Biomechanics: Determining Optimal Technique and Predicting the Effect of Technical Change on Performance

Given the aforementioned limitations with empirical approaches in applied sports biomechanics research, some researchers have resorted to theoretical approaches referred to variously as computer simulation modelling [37], optimal control modelling [38], forward dynamics analysis [39] or, more generically, predictive modelling [40] to putatively establish optimum techniques for individual athletes. Indeed, Sprigings [41] and Irwin [42] have claimed that computer simulation modelling is the *only* true method of determining athlete-specific optimum sports techniques and predicting how various technical changes will impact on performance outcomes for particular athletes. One of the proposed virtues of computer simulation modelling is that it enables one variable to be systematically manipulated, and its effect on the performance criterion to be evaluated, whilst keeping all other variables constant [37]. The manipulation of specific variables in isolation is not feasible in empirical studies, owing to the inherent interconnectedness of the athlete's movement system and the degenerate nature of coordinative structures that underpin sports techniques [43].

An initial first step towards determining athlete-specific optimum techniques using computer simulation modelling is the development of a mathematical model for the athlete under consideration. This model typically includes customised anthropometric, inertial, strength, and viscoelastic parameters based on measurements extracted from the athlete [37]. Once initial conditions have been defined, sets of differential equations representing muscle forces or joint torques are then numerically integrated so that the simulated movement patterns approximate, to within some bounds (see Hicks et al. [44] for details), the movement patterns previously exhibited by the athlete. Finally, these differential equations are further integrated to enable the unique combination of muscle forces or joint torques that maximises the performance criterion to be established. The movement pattern that corresponds with this best combination of muscle forces or joint torques is then deemed to be the optimum technique for that particular athlete.

Despite enthusiastic appraisals about the virtues of computer simulation modelling over the years [45] and some evidence to suggest it can lead to improved sports performance [46], the number of successful examples in the applied sports biomechanics literature is extremely limited. One of the main issues with computer simulation modelling is that the athlete-specific optimum techniques specified are only hypothetical and may not be achievable by the athlete under consideration, despite the best efforts of researchers to customise and validate the mathematical model of that athlete. For example, Felton and King [47] devised a computer simulation model for the front foot contact phase of cricket fast bowling and claimed that ball release speed could be increased by 10–22% depending on whether actual or optimised initial conditions were used during the optimisation process. Given that the teenage fast bowler being studied already had a ball release speed of 35.3 m/s, a 22% increase would translate to a ball release speed of 43.4 m/s, which has only ever been achieved by a very small number of fast bowlers in the history of the sport. Furthermore, it is unclear how adopting the technical changes prescribed by the optimised technique would impact on injury risk for that particular fast bowler. For example, extending the front leg during the front foot contact phase is likely to increase the magnitude, and alter the geometry, of harmful ground reaction forces, potentially leading to lower back injury, which young fast bowlers are known to be particularly susceptible to [48]. As Vaughan [49] warned, it is important to be realistic and not to raise expectations too high when interpreting and applying the results obtained from computer simulation modelling.

A key theoretical construct that explains why some athletes may not be able to achieve their predicted optimum technique, and why attempting to do so may lead to injury, is 'intrinsic dynamics' [50]. In dynamical systems theory, intrinsic dynamics represent the spontaneous coordination tendencies or preferred coordination modes that already exist at the start of the learning process and are shaped by multiple factors, including genes, previous experience, environmental influences, and musculoskeletal architecture, among others. In graphical format, the intrinsic dynamics of a given athlete may be depicted as a series of attractors in a 'dynamic landscape' (see Fig. 4 of Muchisky et al. [51]) with each attractor state corresponding to a particular coordination pattern. It is likely that an athlete will find it difficult to reliably adopt the specified optimum technique if the basin of the existing attractor is deep and/or if the existing and optimum attractors are in different regions of the dynamic landscape. It is important to recognise that athletes are not 'blank slates' [50], and just because an optimum technique can be obtained from computer simulation modelling, it is far from certain whether the athlete under consideration will be able to reliably adopt it, particularly under the often intense psychological pressures of competition, irrespective of the volume of practice undertaken. The capacity of computer simulation modelling to identify achievable athlete-specific optimum techniques may, in part, be improved by incorporating a broader range of constraints, and their non-linear properties, into the mathematical model of the athlete [39].

4 Conclusions

This article has highlighted various issues relating to conventional paradigms in applied sports biomechanics research. It is evident that, contrary to the rhetoric that has featured in some parts of the sports biomechanics literature, the empirical and theoretical approaches commonly adopted in applied sports biomechanics research are unable to reliably identify which aspects of a particular athlete's technique are associated with better performance, nor are they able to reliably predict how performance will change should a particular aspect of an athlete's technique be modified. Even studies that have specifically attempted to identify the technical differences between successful and unsuccessful performances (e.g. Neal et al. [52], Whiteside et al. [53]) have largely been inconclusive. Consequently, the practical application and functional utility of these conventional paradigms from a technique optimisation standpoint is questionable.

It is recommended that both applied sports biomechanists and coaching practitioners should be more circumspect with regard to interpreting the results of applied biomechanics research and have greater awareness of their assumptions and limitations. Sports biomechanists working in high-performance environments, in particular, need to ensure that their own understanding of the data being collected, and underpinning theoretical basis, is correct and that the manner in which this information is disseminated to athletes and their coaches is appropriate. Failure to fulfil either of these requirements could not only lead to a loss of confidence in the data and services being provided, but also the reputation of the sports biomechanist involved, and the credibility of the subdiscipline more broadly.

Compliance with Ethical Standards

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Conflict of interest Paul Glazier and Sina Mehdizadeh declare that they have no conflicts of interest relevant to the content of this article.

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