Human Movement Science 66 (2019) 318–326

Contents lists available at ScienceDirect

Human Movement Science

journal homepage: www.elsevier.com/locate/humov

Training programme designs in professional team sport: An ecological dynamics exemplar

Carl T. Woods[a,*], Ian McKeown[a], Richard J. Shuttleworth[b], Keith Davids[b], Sam Robertson[c]

[a] Port Adelaide Football Club, Football Department, South Australia, Australia
[b] Centre for Sports Engineering Research (CSER), Sheffield Hallam University, Sheffield, UK
[c] Institute for Health and Sport (IHES), Victoria University, Victoria, Australia

ARTICLE INFO

Keywords:
Ecological dynamics
Constraints-led approach
Skill acquisition
Representative learning design
Performance analysis
Interdisciplinarity
Localised interactions

ABSTRACT

Ecological dynamics is a contemporary theory of skill acquisition, advocating the mutuality of the performer-environment system, with clear implications for the design of innovative training environments in elite sport. It contends that performance behaviours emerge, and are adapted, by athletes satisfying a confluence of constraints impacting on their structural and functional capacities, the physics of a performance environment and the intended task goals. This framework implicates contemporary models of coaching, training design and sport science support, to stimulate continuous interactions between an individual and performance environment, predicated on representative learning designs (RLD). While theoretical principles of RLD in ecological dynamics are tangible, their practical application in elite and high level (team) sports need verification. Here, we exemplify how data sampled from a high-performance team sport setting could underpin innovative methodologies to support practitioners in designing representative training activities. We highlight how the use of principles grounded within ecological dynamics, along with data from performance analytics, could suggest contemporary models of coaching and preparation for performance in elite sport.

1. Section 1

1.1. A theoretical background to ecological dynamics

Ecological dynamics is a theoretical framework advocating the mutuality of the performer-environment system, whereby the critical information required for regulation of performance behaviours emerges from continuous interactions that individuals share with a performance environment (Davids, Button, & Bennett, 2008). It blends complexity science and ecological psychology (Kauffman, 1993; Warren, 2006), emphasising the relevance of constraints on behaviours, which have recently been posited as underlying a grand unifying theory of sports performance (Glazier, 2017).

From this perspective, the emergence of movement is predicated on a range of constraints that orient an individual's functional and structural capacities, such as emotional states (Headrick, Renshaw, Davids, Pinder, & Araújo, 2015), the physics of the environment and the intended requirements of the task goal (Davids, Araújo, Vilar, Renshaw, & Pinder, 2013). In performance contexts, such as elite sports, 'skilled intentionality' (Bruineberg & Rietveld, 2014) in an athlete emerges to satisfy key interacting constraints in

* Corresponding author.
E-mail address: cwoods@pafc.com.au (C.T. Woods).

https://doi.org/10.1016/j.humov.2019.05.015
Received 3 March 2019; Received in revised form 6 May 2019; Accepted 14 May 2019
Available online 25 May 2019
0167-9457/

order to functionally achieve a pre-determined task goal (Chow, Davids, Button, & Koh, 2008). An important question concerns how, utilising the conceptualisation of ecological dynamics, practitioners in elite sport can help athletes to develop a deeply integrated relationship between their intentions (goal directed behaviours), perceptions and actions which can support successful performance (Davids, Araújo, Seifert, & Orth, 2015).

Through the lens of ecological dynamics, an athlete or team are viewed as *complex adaptive systems*, where the continuously dynamic and non-linear performer-environment interactions *afford* (provides opportunities for) multiple performance solutions to emerge in achieving the same or similar task goal (Kelso, 2012). The nuanced relationship between multiple performance solutions and the achievement of the same task goal has been conceptualised through the notion of system *degeneracy*, which captures how a system output can be achieved from the use of structurally different elements (Edelman & Gally, 2001). In sport, an exemplar of this concept emerges when a basketballer (re)organises shot type (task goal) based upon his/her current functional and structural capacities (e.g. limb length or upper body power), interacting with key task/environmental constraints (e.g. distance and angle from the hoop, position of a nearest defender and/or the current match score) (Gorman & Maloney, 2016). Skill acquisition has been reconceptualised as skill adaptation in ecological dynamics, defined as a process by which an individual progressively becomes attuned to the relevant affordances (opportunities for action, Gibson (1986)) within a performance environment. This attunement process, with experience and learning, helps athletes to adapt movements to exploit key constraints to functionally achieve a task goal (Araújo, Davids, Chow, Passos, & Raab, 2009).

These insights are founded on fundamental propositions from Nikolai Bernstein (1967), supporting contemporary conceptualisations of how the skilled adaptation of individuals to task demands requires an emphasis on developing *dexterity*. This influential idea for sport practitioners was captured in Bernstein (1967, p. 228) definition of dexterity as *"the ability to find a motor solution for any external situation, that is, to adequately solve any emerging motor problem correctly* (i.e., adequately and accurately), *quickly* (with respect to both decision making and achieving a correct result), *rationally* (i.e., expediently and economically), *and resourcefully* (i.e., quick-wittedly and initiatively)" (italics in the original). Although not conceptualised with sport performance in mind, Bernstein (1967) notion of dexterity is highly relevant for the preparation of team sport athletes interacting with the constraints of the competitive environment.

An implication of this conceptualisation in sport is that learning environments should be (re)designed to offer athletes opportunities to explore and adapt movement solutions under constraints which closely simulate those of competitive performance. When aligned with traditional notions of 'training specificity', this ideology raises significant questions over the design of training practices in elite sport. Traditionally, training specificity refers to the extent to which a practice environment or training activity reflects the demands experienced by an athlete or team during actual competition (Henry, 1968). The 'training specificity hypothesis' contends that the closer a practice task design is to the requirements of competition, the greater the likelihood of a positive learning transfer (Tremblay, 2010). An ecological dynamics approach emphasises the mutuality of the performer-environment system, advocating that training specificity is dependent on the information sources used by athletes to regulate behaviours in competition. An important challenge in sport science is to sample these critical information sources and carefully design them into practice tasks, so they are *representative* of the competitive performance environment (Headrick et al., 2015). Successful sampling of performance data would ensure that the representative design of training activities maintain the coupling between perception and action required within competition, to facilitate athletes in attuning to relevant affordances available within performance environments.

1.2. Representative learning design and the need for contemporary models of coaching in sports

Sport practitioners have been urged to re-consider the way that they prepare athletes for competitive performance, with ecological dynamics proposed as a useful rationale for underpinning this re-consideration process (Ross, Gupta, & Sanders, 2018). However, this type of knowledge transfer would be enhanced by 'real-life' practical examples from elite sport that illustrate how training programmes can be re-designed based on this conceptualisation. In ecological dynamics, an important adjunct to traditional perspectives of training specificity is that of *representative learning design* (RLD) (Brunswik, 1956; Pinder, Davids, Renshaw, & Araújo, 2011). The contention is that practice and training task constraints should be representative of those experienced within a competitive performance environment (Chow, Davids, Hristovski, Araújo, & Passos, 2011). Through RLD, learners will be exposed to relevant affordances within practice, supporting the coupling of their actions to key information sources available in competition (Maloney, Renshaw, Headrick, Martin, & Farrow, 2018; Pinder et al., 2011). In turn, the requisite coupling of information and action in practice implies that representative design of training activities needs to be predicated on task simplification, rather than task decomposition (Davids et al., 2008).

The relationship between an athlete and the competitive performance environment is dynamic and non-linear. Emergent performance solutions are continuously shaped by a confluence of an individual's changing action capabilities (i.e., as they become more experienced, skilful, fitter, faster or stronger), the task goal (which is tailored to the specific demands of a competitive level of performance, based on an athlete's age, experience or 'skill' level) and the competitive environment in which the action is being performed (i.e., familiar or unfamiliar venue; national or international level; culture or geographical location of performance). However, traditionally linear or static methodologies for designing practice activities typically constrain athlete learning behaviours in a very narrow field of the affordance landscape (Davids, Gullich, Shuttleworth, & Araujo, 2017; Rietveld & Kiverstein, 2014). This is because traditional coaching models tend to emphasise the continuous repetition or rehearsal of an ideological (i.e., gold standard) movement pattern within a (somewhat) closed, controlled or predictable practice environment. In contrast, principles of RLD advocate that learning designs should promote opportunities for athletes to engage in the continuous coupling of perception and action and re-organisation of system degrees of freedom, through the stochastic (yet representative) perturbation of behaviours in a variety of practice contexts (Davids et al., 2013, 2017). This conceptualisation of practice designs fundamentally captures Bernstein (1967) notion of practice as 'repetition without repetition' (p. 134).

There is growing empirical work advocating the utility and effectiveness of these contemporary models of preparation for performance grounded in ecological dynamics (Lee, Chow, Komar, Tan, & Button, 2014). Through careful task and instructional constraint manipulation, Lee et al. (2014) demonstrated that exploiting system degeneracy (capacity for re-organisation of system degrees of freedom) was an effective strategy for acquiring sport skills in contrast to methods advocated in traditional linear models. Specifically, through the encouragement of functional movement variability, and appreciation of multi-stability (one cause resulting in multiple possible behavioural effects), learners demonstrated greater exploratory tendencies and movement repertoire to achieve a task goal, relative to a traditional linear model of skill acquisition informed by an ideological and prescriptive movement pattern (Lee et al., 2014).

The findings of work such as Lee et al. (2014) signals the need for athlete preparation models which promote representativeness within learning designs and effective use of task simplification strategies, advocating that practitioners sample information from a competitive performance environment to ensure a functional coupling between perception-action (Maloney et al., 2018; Pinder et al., 2011). A key challenge in these innovative performance preparation models is for sports practitioners to access patterns of data from competitive performance to sustain high levels of evidence-based functionality within training programmes. This deep integration of theory and data would support a performer in achieving intended task goals through the adaptability of their behaviours, guided by the same (or highly similar) information sources encountered within competition (Araújo, Davids, & Passos, 2007; Pinder et al., 2011). To achieve this challenge, training activities need to be high in action fidelity, so that an emerging performance solution is reflective of a solution that is evidently functional in competition (Davids et al., 2013). A key implication of this model of preparation for performance in competition is that training activities with a narrow range of affordances, which may be low in functionality and action fidelity, will likely hinder an athlete's capability to attune to relevant affordances within competition, possibly limiting learning transfer (Araújo et al., 2007).

While, theoretically, principles of RLD are compelling and readily understandable, a challenge for sports practitioners is to consider how training activities can be designed to be representative of competitive performance environments. Practically, *how can relevant information sources be sampled from competitive performance environments, and how can this information be designed into practice activities to allow a coach to monitor and progress representativeness in learning?* The nature and qualitative characteristics of specialised training are fundamentally important applied issues of theoretical relevance to sports practitioners at all levels of performance. These issues are aligned with insights of contemporary models of sports training, such as the Athletic Skills Model (ASM) (Wormhoudt, Savelsbergh, Teunissen, & Davids, 2018). The ASM proposes that specialised athlete training should be highly focused on development of adaptive skills by providing opportunities for the self-regulation of athletes in challenging practice designs that simulate competitive performance environments (termed 'sport adaptive training').

1.3. A constraints-led approach to preparation for performance in team sport

1.3.1. Synergy formation

In ecological dynamics, synergy formation is a fundamental property of a complex adaptive system. Dynamical interactions between team sports players can be shaped bi-directionally: *global to local* and *local to global* (Ribeiro, Silva, Duarte, Davids, & Garganta, 2017). Traditional models of preparation for performance emphasise global to local interactions, exemplified by an external agent such as a coach, prescribing in advance tactical and strategical patterns of behaviours to team players in attack and defence. In contrast, in nature, there are many examples of rich patterns of behaviour emerging in complex adaptive systems in a local to global direction. Rich, global patterns of system behaviour, exemplified by murmuration's in flocking birds (https://vimeo.com/31158841), schooling in fish and nest-building behaviours of colonies of insects, emerge from self-organised, localised interactions between individual organisms. These bi-directional constraints on synergy formation in athletes and sports teams subsequently shape coordinative patterns at both intra (within an athlete) and inter (between athletes) individual levels by providing the 'boundaries' in which movement solutions emerge (Newell, 1986; Passos, Araújo, Davids, & Shuttleworth, 2008).

Effective implementation of representative learning environments to harness local interaction tendencies in team games players can be guided by sampled constraints that shape the behaviours within competition (Renshaw, Chow, Davids, & Hammond, 2010). Knowledge of the key interacting constraints associated with successful performance in a sport will help practitioners to representatively manipulate them within a practice task. This challenge leads to the second component needed to answer the overarching practical question posed in this paper: *Using their experiential knowledge, how can practitioners sample key task constraints from a competitive performance environment?*

1.3.2. Sampling constraints

In a contemporary model of athlete preparation, there is a need to sample constraints on performance of individual performers, using an interdisciplinary approach. It is common for sports performance analysts to quantify specific actions that occur within competition in an attempt to identify desirable (and undesirable) actions that relate to the achievement of a predetermined outcome via notational analysis (for examples, refer to Robertson, Back, & Bartlett, 2015; Woods, Sinclair, & Robertson, 2017). However, a common criticism of this work is that is does not provide a coach with the contexts in which identified actions occur (Glazier & Robins, 2013). For example, Woods et al. (2017) identified the performance indicators (and subsequent frequency counts) that were important for successful team performance in elite rugby league, but an analysis of the surrounding constraints that shaped the emergence of these actions was not provided. Provision of contextual information to underpin analysis of action specificity and frequency would enhance training designs, emphasising an individualised approach. Without it, practitioners may over-rely on average values in performance measures and be challenged to effectively manipulate constraints in training to enhance RLD, incorporate functional variability within individualised training activities and attune athletes to relevant affordances.

To achieve this critical aim in elite sport, groups of practitioners, including performance analysts, coaches, psychologists, sport scientists and skill acquisition specialists, could collaborate on designing individualised practice task constraints based on competitive performance data. This collaborative, interdisciplinary approach would help identify performance behaviours (considered at different levels of analysis) evidenced as important for successful team outcomes (product), as well as the task, individual and environmental constraints that shape their emergence (process). This concept was recently discussed by Farrow and Robertson (2017) in their description of how to periodise the acquisition of skills within high performance sport. They provided a hypothetical example of how a coach may ascertain a 'training specificity' value by contrasting the constraints of competition against those of a training activity. Practitioners could, therefore, utilise this 'specificity' value to determine how *representative* a training activity is, as well as using it as a basis for implementing the principles of overload (e.g. making the task goal more (or less) challenging for the athlete based on its 'specificity' relative to competitive performance) (Farrow & Robertson, 2017).

In the remaining sections of this paper, we explore an example from a professional sports training programme in which the principles of RLD and the constraints-led framework were considered in the design of a training activity. Specifically, in this example we utilise data collected from an elite Australian football (AF) performance landscape. Its intention is to illustrate how a scientific conceptualisation of potential training designs could provide an applied rationale for practitioners to consider how key principles of RLD could be used to enhance the links between practice and performance. Our aim is to inspire sport practitioners to consider adapting current pedagogical methodologies based on theory and data presented.

2. Section 2 – What would such a model of athlete support look like? Representative design of kicking practice in Australian football

2.1. Background

Within AF, there are two primary modes of ball disposal underpinning interactions between teammates – a kick and a handball. Successful performance of both actions (defined by the ball being passed to a teammate without impedance from an opponent) is critical to team success within the Australian Football League (AFL; elite AF competition) (Robertson et al., 2015). Here, the performance goal of ball passing to a teammate via a kick was considered central to a 'skill acquisition' programme at a professional AF club (for readers unfamiliar with ball passing in AF, refer to the link https://womensfooty.com/files/training/skills_guide.pdf). Conceptualising players as *complex adaptive systems*, it was appreciated that the organisation of these actions was predicated on a confluence of performer, environmental and task constraints. Accordingly, training such actions was designed within a performance landscape that afforded high functionality and action fidelity. These features of learning design encouraged players to functionally adapt their kicks, when interacting with a representative context that simulated the demands of competition to which functional adaptations were regularly needed.

This approach to training design shifted the coach's role from the more traditional provider of augmented, corrective verbal instructions on movements (typically biased towards a putative 'ideological' technique). Instead coaches evolved into architects of representative performance problems (referred to as a learning environment designer), predicated on challenges imposed primarily by the specific patterns of play and performance tendencies of opposition during competitive performance. Given this specific need, the synergy formation that was encouraged to emerge within the practice activities was shaped from *local to global* tendencies, in which the patterns of behaviour were resultants of the activity design, rather than from an external agent (i.e., coach). Practice activities therefore transitioned from static, narrowly afforded landscapes, to players being challenged to self-organise performance behaviours to achieve task goals (capturing *skilled intentionality*). To instantiate this contemporary model of athlete preparation for performance, we set out to sample the key constraints that specifically shaped kicking within AF, and relate the representativeness of these constraints to a training activity intended to stimulate kicking performance.

2.2. Methodology

Using the constraints-led framework proposed by Newell (1986), three elite coaches (defined by coaching within the AFL for more than five years), who were familiar with a constraints-led approach, were asked to heuristically select key constraints split across each category (performer, environment and task) that they considered as influential on kicking skill in AF performance. The outcomes of this consensus are provided in Table 1. Following this, a performance analyst quantified these constraints within a sample of ten AFL matches via notational analysis software (Sportscode version 11.2.18, Sportstec Inc. Warriewood NSW). Briefly, possession time (task constraint) was calculated as the time between the player first obtaining ball possession to the time of kick execution. We then split this into two components – a kick in general play and a kick from a mark or stoppage, in four temporal epochs. Environmental constraints were defined by the number of opponents within a 3 m radius of the ball carrier at the point of kick (ball carrier density) and the intended receiver of the kicked pass at the point of ball reception (receiver density). Performer constraints were defined relative to the locomotive characteristics of the kicker at the point of kick – defined as stationary (standing still or walking) or dynamic (jogging or running). To capture the notion of 'repetition without repetition', we transformed the counts of the kicks in each constraint category to represent a percentage of the total kicks performed (e.g. if six kicks were afforded within a processing time of 1–2 s from a total of 10, this value would equate to 60% of kicks in this constraint category) (Farrow & Robertson, 2017). In this

Table 1
The constraint matrix used within the current study.

Constraint class	Constraint	Description	Sub-category label
Task	General play possession time	Time between a player obtaining and then disposing of the ball while in general play (i.e., not from a 'mark' or 'free kick')	0–1 s 1–2 s 2–3 s > 3s
	Stoppage possession time	Time between a player obtaining the ball from a stoppage in play ('mark' or 'free kick') and then disposing of it	0–1 s 1–2 s 2–3 s > 3s
Environmental	Target density	Number of opposition players within a 3 m radius of the intended disposal target	Uncontested Even (e.g. 1 v 1) Superior (e.g. 2 v 1) Inferior (e.g. 1 v 2)
	Ball carrier density	Number of opposition players within a 3 m radius of the ball carrier at ball disposal	Unpressured 1 Opposition Player 2 Opposition Players 3 Opposition Players > 3 Opposition Players
Individual	Disposal movement	Locomotive state at point of ball disposal	Stationary (e.g. walking) Dynamic (e.g. running)

Note: 's' denotes seconds, 'm' denotes metres.

example, the data sampled from these ten AFL matches were then averaged to provide a basis for the influence of each constraint. Following this process, we designed a training activity that had an intended focus on stimulating kicking performance, and applied the same notational analysis and data transformation process across ten occurrences of this activity.

2.3. Applied examples

In the following sections, we provide three univariate ways in which a coach may consider visualising, analysing and measuring the results when determining the representativeness of a training activity. Each of these techniques are founded upon recommendations proposed within the existing literature (Farrow & Robertson, 2017), and have been chosen and adapted to suit their utility within a high-performance sport setting.

2.3.1. Example 1 – Data visualisation

The data were plotted using a scatterplot overlaid with a violin plot to show the data distribution. These plots show the density distributions of the data and provide a simple visualisation of the data with respect to skewness and modality. Interpretation of these plots requires little analytical expertise, thus making them useful for most practitioners, who need quick, effective and efficient methods for understanding how performance data may underpin practice designs.

Fig. 1 contrasts the relative proportions of kicks performed in each constraint category between an AFL match and a training activity. Each dot represents a training or match observation, which allows a practitioner to investigate representativeness at an individual training activity level, as opposed to observing trends using a mean value. From their interpretation, practitioners can quickly identify constraints and training sessions that generate a "training performance mismatch" (contrasting with the specificity of training principle), which could subsequently form the basis of practice re-design through informed constraint manipulation. A practitioner can subjectively denote thresholds for a "training-performance mismatch value", which when transitioned away from, may require activity re-design. For the premise of this example, we considered a training mismatch value of 10%. Based on this value, a large proportion of training-performance mismatches can be observed within the percent of kicks performed < 1 s in general play, the dynamic and stationary categories, kicks performed without opponent pressure, with two and three opponents surrounding the ball carrier, and performed to a receiver uncontested or who is outnumbered by immediate opponents (Fig. 1). These data were, therefore, used by practitioners to manipulate the task constraints of a training activity to enhance its representativeness by decreasing the number and severity of training-performance mismatches.

2.3.2. Example 2 – Magnitude-based analysis

Although use of a "training-performance mismatch value" and accompanying visualisation are relatively simple and require little analytical expertise, they are primarily based upon subjective interpretation. A magnitude-based statistical analysis, such as effect size calculations, could be performed to ascertain the magnitude of observed differences. The effect size (d) of observed differences could then be used to assist a practitioner with the use and interpretation of the "training-performance mismatch value". Using effect size interpretations (Hopkins, 2010), we applied this analysis to our dataset, as presented in Table 2. Results imply that medium and large differences are present for at least 12 constraints comparisons. Such insight allowed coaches to longitudinally determine the standardized magnitude of training-performance mismatch following targeted constraint manipulation and activity re-design.

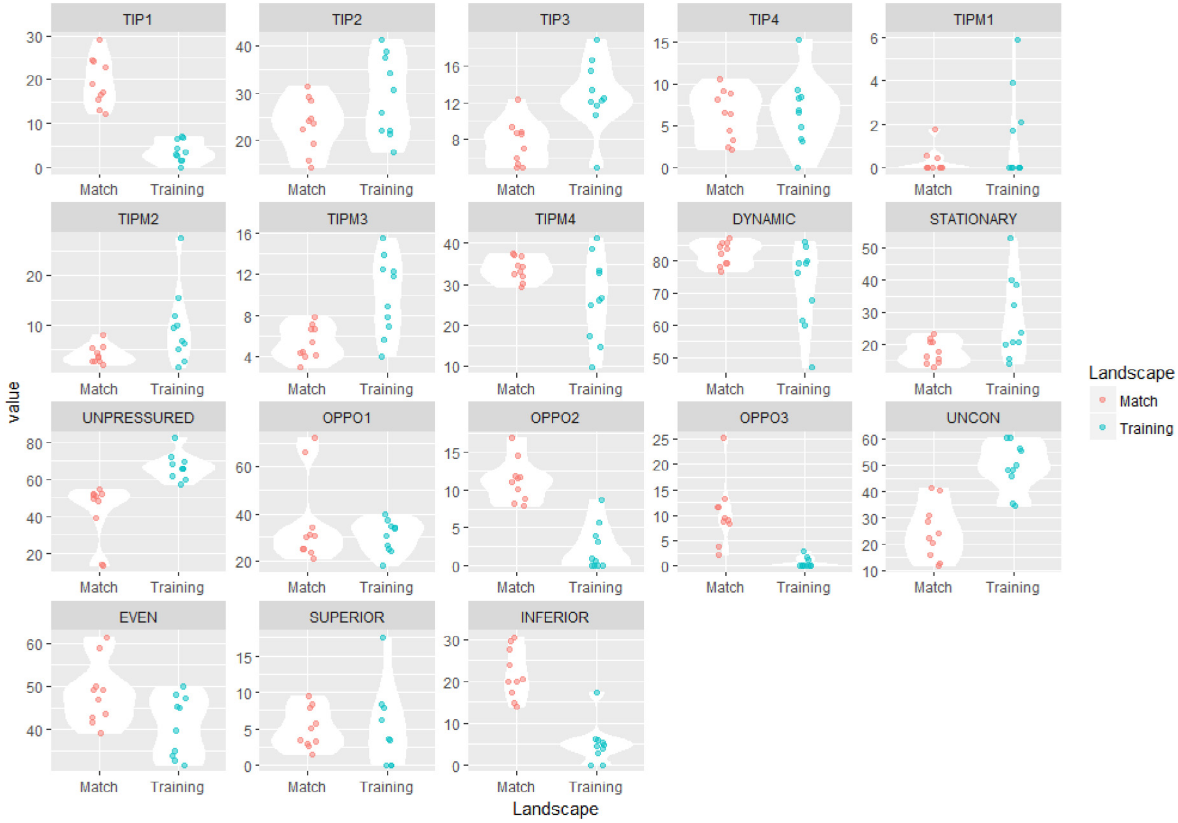

Fig. 1. Violin plot showing the distributional differences in constraint values between matches and the training activity. Note, "TIP" denotes time in possession, "TIPM" denotes time in possession from a mark or stoppage in play, "OPPO" denotes opposition, "UNCON" denotes uncontested.

Table 2
Descriptive statistics and effect sizes (90% CI) for each constraint *Note*; "GP" denotes general play processing time, "M" denotes processing time from a mark, and "CI" denotes confidence interval.

Constraint Class	Constraint	Training (%)	Match (%)	Effect Size (*d*)
Task	GP < 1 s	4	19	3.68 (2.40–4.89)
	GP 1–2 s	29	23	0.82 (0.04–1.57)
	GP 2–3 s	13	8	1.65 (0.77–2.50)
	GP > 3 s	7	6	0.11 (−0.84–0.62)
	M < 1 s	1	1	0.71 (0.05–1.46)
	M 1–2 s	10	4	1.03 (0.23–1.80)
	M 2–3 s	10	5	1.56 (0.69–2.39)
	M > 3 s	27	34	0.95 (0.15–1.71)
Individual	Dynamic	72	82	1.07 (0.27–1.85)
	Stationary	28	18	1.07 (0.27–1.85)
Environment	Unpressured	67	42	1.99 (1.05–2.88)
	1 Opponent	30	36	0.40 (−0.34–1.14)
	2 Opponents	2	11	3.08 (1.94–4.17)
	> 3 Opponents	1	10	2.17 (1.21–3.10)
	Uncontested	49	25	2.48 (1.45–3.45)
	Even	41	48	1.04 (0.24–1.82)
	Superior	5	5	0.03 (−0.77–0.69)
	Inferior	5	22	3.09 (1.94–4.18)

2.3.3. Example 3 – Quantifying training representativeness

Another means in which sport practitioners could measure, analyse and utilise these data could be to use the technique described by Farrow and Robertson (2017). They proposed a "specificity difference" by subtracting the relative value of a training activity from the match or a performance competition value. By then summating these values for each constraint category, dividing by half and then subtracting from 100% (they denoted 100% as hypothetical 'complete representativeness'), the practitioner obtained an

Table 3
Constraint comparison matrix.

Constraint Class	Constraint	Training (%)	Match (%)	Specificity Difference (%)
Task	GP < 1 s	4	19	−15
	GP 1–2 s	29	23	6
	GP 2–3 s	13	8	5
	GP > 3 s	7	6	1
	M < 1 s	1	1	0
	M 1–2 s	10	4	6
	M 2–3 s	10	5	5
	M > 3 s	27	34	−7
	Representative Value			**77%**
Individual	Dynamic	72	82	−10
	Stationary	28	18	10
	Representative Value			**90%**
Environment	Unpressured	67	42	24
	1 Opponent	30	36	−6
	2 Opponents	2	11	−9
	> 3 Opponents	1	10	−9
	Uncontested	49	25	24
	Even	41	48	−7
	Superior	5	5	0
	Inferior	5	22	−16
	Representative Value			**61%**

Note: "GP" denotes general play processing time, and "M" denotes processing time from a mark.

objective measure of how representative that constraint category is, relative to competitive performance constraints. Table 3 shows an application of this analysis to the present dataset. It is noteworthy that the most representative constraint class was the *performer* (representative value of 90%) and the least was *environment* (representative value of 61%). In addition to assisting with training activity design and informed constraints manipulation, these values could be used as a basis for training periodisation, specifically guiding the principles of overload (Farrow & Robertson, 2017). Indeed, what is considered as an 'acceptable' representative value is subjective, based on a preconceived activity plan initially composed by sport practitioners.

2.4. Future directions and avenues for adapting our applied examples

These three examples provide a feasible means of quantifying training designs relative to the demands of competitive performance environments. However, it is important to acknowledge that constraints do not operate in isolation to one another; rather, they dynamically interact to shape the emergent, adaptive behaviour (Renshaw et al., 2010). Increasing (or decreasing) the representativeness of one constraint class is likely to impact on another constraint class. For example, a kick performed within a game from a mark > 3 s in duration (task constraint) will likely be accompanied by a reduction in physical pressure imposed by an opponent. Comparatively, a kick performed in general play with an organisation time of < 1 s will likely be accompanied by considerable physical pressure imposed by an opponent. Thus, training each constraint class in isolation may limit the representativeness of an activity, which may limit performance transfer. Accordingly, providing context to these constraint interactions will likely increase the representativeness of activities intended to improve kicking performance.

Unfortunately, linear analytical approaches (as described earlier) are unable to discern such contextual patterns amongst the constraints interactions. To counter this issue, machine learning is progressively becoming commonplace in sport science (both academically and practically), providing a capacity to resolve complex non-linear patterns within large, multivariate datasets (for examples, refer to Robertson et al., 2015; Woods et al., 2017). As an exemplar of the aforementioned problem, Robertson, Spencer, Back, and Farrow (2018) recently applied rule induction to contextualise the interaction of constraints that shape kicking within AF. Rule induction is a machine learning technique capable of resolving complex patterns within large transactional datasets (Agrawal & Srikant, 1994). In that study, a kick was viewed as a transactional event that occurred at a specific point in time, which consisted of multiple items (or constraints) that shaped its emergence. This approach was subsequently able to resolve the common constraint interactions shaping the emergence of certain kicks. For example, a kick performed with an organisation time of < 2 s was typically executed while stationary, over a distance > 40 m, and to a teammate with an adjacent opponent (Robertson et al., 2018). Sports practitioners could use this information to further enhance the representativeness of their training activities by supporting greater contextualisation of the designs utilising constraints interactions. However, such a non-linear approach requires sound analytical expertise, furthering our stance of RLD requiring interdisciplinary collaboration – a skill acquisition specialist grounding practice in sound theoretical constructs, coaches providing experiential expertise into key constraints shaping a behaviour, and an analyst sampling and modelling data in a meaningful and practical manner.

2.4.1. General conclusion

In this paper, we provided a theoretical basis for contemporary models of training design grounded in ecological dynamics.

Accompanying this interpretation, we presented an applied example that incorporated 'real-world' performance data to demonstrate how sport practitioners may consider applying the principles of RLD within a high-performance setting. This integration of theory and practice could provide sport practitioners with a sound theoretical and practical basis for which to design practice activities that offer closer representations of affordances available to an athlete within a competitive performance environment. While there are growing bodies of empirical work testing the principled contentions of RLD (for examples, see Maloney et al., 2018; Pinder et al., 2011; Robertson et al., 2018), more applied work is needed if the sub-discipline of sports skill acquisition, along with related areas of performance analysis, strength and conditioning, psychological support and coaching, is to continue to innovate models for athlete preparations for high-performance sport.

Author contributions

CW, SR, IM and K_D conceptualised the idea, CW analysed the data, CW, IM, SR, K_D and RS wrote and drafted the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.humov.2019.05.015.

References

Agrawal, R., & Srikant, R. (1994). Fast algorithms for mining association rules in large databases. *Proceedings of the 20th international conference on very large data bases* (pp. 487–499). Santiago de Chile: VLDB.

Araújo, D., Davids, K., & Passos, P. (2007). Ecological validity, representative design, and correspondence between experimental task constraints and behavioural setting: Comment on Rogers, Kadar, and Costall (2005). *Ecological Psychology, 19*, 69–78.

Araújo, D., Davids, K., Chow, J. Y., Passos, P., & Raab, M. (2009). The development of decision making skill in sport: An ecological dynamics perspective. In D. Araújo, & H. Ripoll (Eds.). *Perspectives on COGNITION AND ACTION IN SPORT* (pp. 157–169). Suffolk, United States of America: Nova Science Publishers Inc.

Bernstein, N. (1967). *The co-ordination and regulations of movements.* Oxford: Pergamon Press.

Bruineberg, J., & Rietveld, E. (2014). Self-organization, free energy minimization, and optimal grip on a field of affordances. *Frontiers in Human Neuroscience, 12*, 599–613.

Brunswik, E. (1956). *Perception and the representative design of psychological experiments* (2nd ed.). Berkeley, CA: University of California Press.

Chow, J. Y., Davids, K., Button, C., & Koh, M. (2008). Coordination changes in a discrete multi-articular action as a function of practice. *Acta Psychologica, 127*, 163–176.

Chow, J. Y., Davids, K., Hristovski, R., Araújo, D., & Passos, P. (2011). Nonlinear pedagogy: Learning design for self-organizing neurobiological systems. *New Ideas in Psychology, 29*, 189–200.

Davids, K., Araújo, D., Seifert, L., & Orth, D. (2015). Expert performance in sport: An ecological dynamics perspective. In J. Baker, & D. Farrow (Eds.). *Routledge international handbooks. Routledge handbook of sport expertise* (pp. 130–144). New York, NY, US: Routledge/Taylor & Francis Group.

Davids, K., Araújo, D., Vilar, L., Renshaw, I., & Pinder, R. (2013). An ecological dynamics approach to skill acquisition: Implications for development of talent in sport. *Talent Development and Excellence, 5*, 21–34.

Davids, K., Gullich, A., Shuttleworth, R., & Araújo, D. (2017). Understanding environmental and task constraints on talent development: analysis of micro-structure of practice and macro-structure of development histories. In J. Baker, S. Cobley, J.. Schorer, & N. Wattie (Eds.). *Routledge handbook of talent identification and development in sport* (pp. 192–206). Abingdon, Routledge: Routledge International Handbooks.

Davids, K., Button, C., & Bennett, S. J. (2008). *Dynamics of skill acquisition: A constraints-led approach.* Champaign, IL: Human Kinetics.

Edelman, G. M., & Gally, J. A. (2001). Degeneracy and complexity in biological systems. *Proceedings of the National Academy of Sciences of the United States of America, 98*, 13763–13768.

Farrow, D., & Robertson, S. (2017). Development of a skill acquisition periodisation framework for high-performance sport. *Sports Medicine, 47*, 1043–1054.

Gibson, J. J. (1986). *An ecological approach to visual perception.* Boston, MA: Houghton-Mifflin.

Glazier, P. (2017). Towards a grand unifying theory of sports performance. *Human Movement Science, 56*, 139–156.

Glazier, P., & Robins, M. (2013). Self-organisation and constraints in sports performance. In McGarry, O'Donoghue, & Sampaio (Eds.). *Routledge handbook of sports performance analysis* (pp. 42–52). London: Routledge.

Gorman, A. D., & Maloney, M. A. (2016). Representative design: Does the addition of a defender change the execution of a basketball shot? *Psychology of Sport and Exercise, 27*, 112–119.

Headrick, J., Renshaw, I., Davids, K., Pinder, R. A., & Araújo, D. (2015). The dynamics of expertise acquisition in sport: The role of affective learning design. *Psychology of Sport and Exercise, 16*, 83–90.

Henry, F. M. (1968). Specificity vs. generality in learning motor skill. In R. C. Brown, & G. S. Kenyon (Eds.). *Classical studies in physical activity* (pp. 328–331). Englewood Cliffs: Prentice-Hall.

Hopkins, W. G. (2010). A new view of statistics. *Sportscience*. http://www.sportsci.org/resource/stats.

Kauffman, S. A. (1993). *The origins of order: Self-organization and selection in evolution.* Unitied Kingdom: Oxford University Press.

Kelso, J. A. (2012). Multistability and metastability: Understanding dynamic coordination in the brain. *Philosophical Transactions of the Royal Society B, 367*, 906–918.

Lee, M. C., Chow, J. Y., Komar, J., Tan, C., & Button, C. (2014). Nonlinear pedagogy: An effective approach to cater for individual differences in learning a sports skill. *PLos One, 9*, e104744.

Maloney, M. A., Renshaw, I., Headrick, J., Martin, D. T., & Farrow, D. (2018). Taekwondo fighting in training does not simulate the affective and cognitive demands of competition: Implications for behavior and transfer. *Frontiers in Psychology,* 9.

Newell, K. M. (1986). Constraints on the development of coordination. In M. G. Wade, & H. T. A. Whiting (Eds.). *Motor development in children: aspects of coordination and control* (pp. 341–360). Dordrecht, The Netherlands: Martinus Nijhoff.

Passos, P., Araújo, D., Davids, K., & Shuttleworth, R. (2008). Manipulating constraints to train decision making in rugby union. *International Journal of Sport Science and Coaching, 3*, 125–140.

Pinder, R., Davids, K., Renshaw, I., & Araújo, D. (2011). Representative learning design and functionality of research and practice in sport. *Journal of Sport & Exercise Psychology, 33*, 146–155.

Renshaw, I., Chow, J. Y., Davids, K., & Hammond, J. (2010). A constraints-led perspective to understanding skill acquisition and game play: A basis for integration of motor learning theory and physical education praxis? *Physical Education and Sport Pedagogy, 15*, 117–137.

Ribeiro, J., Silva, P., Duarte, R., Davids, K., & Garganta, J. (2017). Team sports performance analysed through the lens of social network theory: Implications for research and practice. *Sports Medicine, 47*, 1689–1696.

Rietveld, E., & Kiverstein, J. (2014). A rich landscape of affordances. *Ecological Psychology, 26*, 325–352.

Robertson, S., Back, N., & Bartlett, J. (2015). Explaining match outcome in elite Australian Rules football using team performance indicators. *Journal of Sports Sciences,* *34*, 637–644.

Robertson, S., Spencer, B., Back, N., & Farrow, D. (2018). A rule induction framework for the determination of representative learning design in skilled performance. *Journal of Sport Sciences*.

Ross, E., Gupta, L., & Sanders, L. (2018). When research leads to learning, but not action in high performance sport. *Progress in Brain Research, 240*, 201–217.

Tremblay, L. (2010). Visual information in the acquisition of goal-di-rected action. In D. Elliott, & M. Khan (Eds.). *Vision and goal-directed movement neurobehavioral perspectives* (pp. 281–291). Human Kinetics: Champaign.

Warren, W. H. (2006). The dynamics of perception and action. *Psychological Review, 113*, 358–389.

Woods, C. T., Sinclair, W., & Robertson, S. (2017). Explaining match outcome and ladder position in the National Rugby League using team performance indicators. *Journal of Science and Medicine in Sport, 20*, 1107–1111.

Wormhoudt, R., Savelsbergh, G., Teunissen, J. W., & Davids, K. (2018). *The athletic skills model: Optimizing talent development through movement education.* London: Routledge.