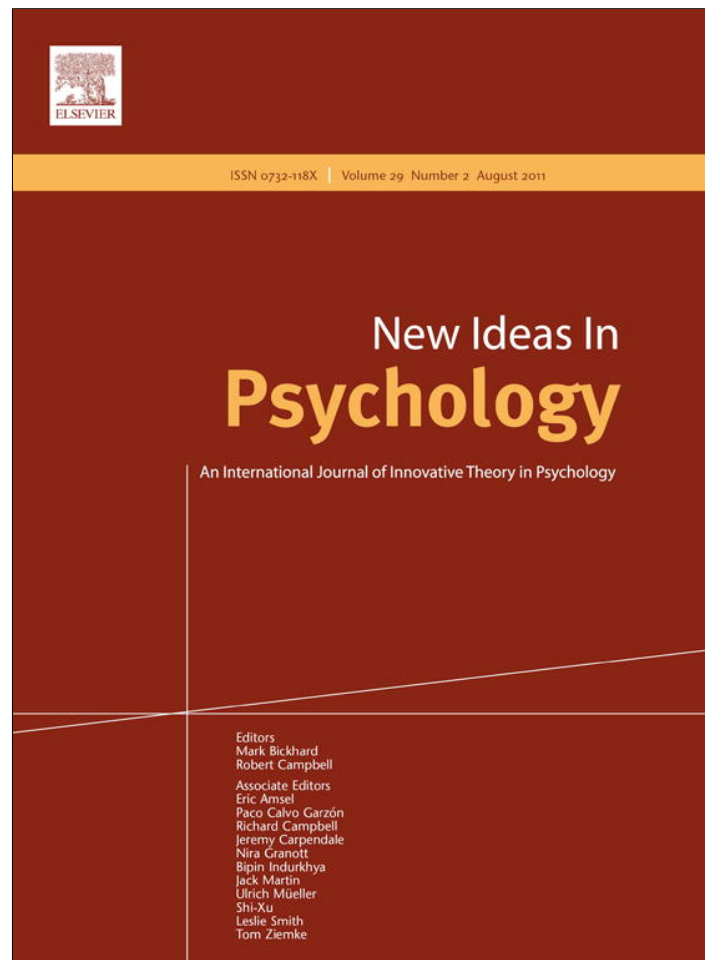


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Nonlinear pedagogy: Learning design for self-organizing neurobiological systems

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In this paper, key concepts in ecological psychology and nonlinear dynamics exemplify how learning design can be shaped by ideas of self-organization, meta-stability and self-organized criticality in complex neurobiological systems. Through interactions with specific ecological constraints in learning environments, cognition, decision making and action emerge. An important design strategy is the use of different types of noise to channel the learning process into meta-stable regions of the “learner–learning environment” system to encourage adaptive behaviors. Here learners can be exposed to many functional and creative performance solutions during training. Data from studies in the performance context of sports are used to illustrate how these theoretical ideas can underpin learning design. Based on these insights a nonlinear pedagogy is proposed in which the role of coaches or trainers alters from a more traditional, prescriptive stance to the mode of manipulating key interacting task constraints including information, space and equipment to facilitate learning.

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1. Introduction

Neurobiological system indeterminacy has been exemplified in ‘situated’ perspectives on learning, providing valuable insights on the development of an embodied cognition (e.g., Clark, 1997, 1999, 2001; Varela, Thompson, & Rosch, 1995). The Cartesian view of separating cognition and body is considered reductive, requiring revision since the learner may be better conceptualized as an integrated, complex system (Kelso & Engström, 2006; Port & van Gelder, 1995; Tschacher & Dauwalder, 2003). Learning takes place in dynamic contexts and the acquisition of knowledge occurs as a consequence of indeterminate interactions between learners and the environment (Barab & Kirshner, 2001).

These advances in embodied cognition emphasize the learner–environment relationship. This systemic approach is harmonious with contemporary work on motor performance and skill acquisition, influenced by concepts in ecological psychology and nonlinear dynamics such as information–action coupling, self-organization, constraints, emergence, variability and stability of behavior in neurobiological systems (see Davids, Button, & Bennett, 2008; Handford, Davids, Bennett, & Button, 1997; Kelso, 1995; Newell, Liu, & Mayer-Kress, 2008; Warren, 2006). Alternative conceptualizations of processes of perception, cognition, decision making and action have emerged for studying intentional behavior in complex, self organizing, neurobiological systems functioning in dynamic environments (e.g., Van Orden, Holden, & Turvey, 2003). This *ecological dynamics* rationale proposes that the most relevant information for performance and learning in dynamic environments arises from continuous performer–environment interactions (Araújo, Davids, & Hristovski, 2006; Raczaszek-Leonardi &

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Kelso, 2008; Van Orden et al., 2003). In ecological dynamics, the coupling of perception and action sub-systems is based on the mutuality and reciprocity of neurobiological systems and their environments. Under this synergy, insights from psychology, biology and physics have been integrated to enhance understanding of how neurobiological systems function adaptively in their eco-niches (e.g., Davids & Araújo, 2010; Davids, Button, Araújo, Renshaw, & Hristovski, 2006; Warren, 2006). Performance and learning are constrained by key features of the organism–environment system including the structure and physics of the environment, the biomechanics and morphology of individual and specific task constraints. Adaptive, goal-directed behavior emerges as neurobiological systems attempt to satisfy these interacting constraints. For these reasons, ecological dynamics proposes that the study of neurobiological cognition and action should avoid ‘organismic asymmetry’ (Dunwoody, 2007) and instead should be aimed at “...phenomena within the organism–environment synergy rather than within the organism per se.” (Beek & Meijer, 1988, p. 160; see also Turvey & Shaw, 1995).

Developing a sound theoretical rationale for identifying and manipulating the major constraints on learners provides a principled basis for the design of learning programs (e.g., Araújo, Davids, Bennett, Button, & Chapman, 2004; Davids et al., 2008). These ideas suggest that psychologists, educators and trainers should act as facilitators to guide learners’ exploratory activities as they seek to assemble solutions for pre-specified action goals (see Barab et al., 1999). In this view, the individual learner is an independent component amongst an array of influential constraints within the learner–environment system. The emergence of learning is closely coupled to the type of constraints present in the specific performance context (Kelso, 2008). In nonlinear dynamics it has been shown how complex neurobiological systems continuously adapt and change their organizational states through processes of spontaneous self-organization (Kelso, 1995; Newell et al., 2008; Thelen, 2000). These ideas are predicated on analyses of evolutionary complex systems demonstrating how they transit between states of ordered stability and instability as they adapt to changing constraints (e.g., Kauffmann, 1995). Meta-stability is an important characteristic observed in complex systems when they are poised between states of order and instability (Kelso, 2008). Meta-stable states have been defined as ‘dynamically stable’ states which allow systems to remain poised between stability and instability (Kelso, 1995). It has been observed that, in the meta-stable state, rich interactions can spontaneously emerge within complex systems when previously uncorrelated system components or processes suddenly become interconnected under constraints (Guerin & Kunkle, 2004; Juarrero, 1999). Meta-stable states in complex neurobiological systems are significant because varied and creative patterns of behavior can emerge as individual system components co-organize or co-adapt as specific goals are achieved.

In the study of learning design, it is important to understand how meta-stability in neurobiological systems can be harnessed to facilitate learning and system change along different timescales (Hristovski, Davids, & Araújo,

2006, 2009; Passos et al., 2008). In this paper we propose how the idea of ‘co-adaptive moves’ in the meta-stable region of complex systems can contribute to our understanding of learning design (Kauffmann, 1995), and we illustrate how these ideas can be integrated in a nonlinear pedagogy.

2. Key differences between linear and nonlinear systems

We start by identifying some major differences between linear and nonlinear systems in nature. In linear dynamics, a large change in a system’s behavior needs to be preceded by a large change in its cause(s). In nonlinear dynamics a minute change in system (micro) dynamics may also produce large, even qualitative changes in the system’s (macroscopic) behavior or performance. In other words, a linear system’s behavior is always proportional to its causes, while nonlinear systems can demonstrate both types of properties. Many systems studied in science are nonlinear in nature, although they have been traditionally studied with the so-called *linear approximation method* (i.e., in a linear regime) because that has been easier for analytical purposes. In short: cause-effect proportionality is a hallmark of linear behavior and *non-proportionality* is a hallmark of nonlinear system behavior. A major implication of this key idea for learning design is that small changes to practice task constraints, such as information present or technical changes to equipment, may result in significant changes in learners’ behaviors.

A second, important difference between these two broad classes of systems is that in linear systems, a single cause can generate only one behavioral effect, while in nonlinear systems one cause may have multiple behavioral effects. That is, linear systems are always *mono-stable* and nonlinear systems may be *mono-* and *multi-stable*. In nonlinear systems, the property of multi-stability can be observed through careful manipulation of system parameters. The capacity to alter system parameters is considered as the third characteristic of nonlinear systems with an emphasis on *parametric control*. Parametric control implies that by changing specific parameters, coaches or trainers can effectively guide a learning system to explore the functionality of different organizational states. This strategy will expose a learning system to task variability to discover functional states of organization in adapting to environmental and task constraints.

A related characteristic which differentiates linear and nonlinear systems is the role of ‘noise’ in the system. Traditionally, noise is defined as an uncontrollable part of system dynamics, which has led to it being viewed as undesirable in control systems analyses. In linear systems, which are *mono-stable*, noise almost always plays a detrimental role in producing undesired system output variability (e.g., Broadbent, 1958). In contrast, in *multi-stable* nonlinear, dynamical systems, noise can play a functional role by enhancing the probability of system transition between multiple states. The interjection of noise or signal variability can contribute to the exploration of multiple solutions to a performance goal by a learning system. In this way noise has the capacity to enhance the flexibility of a learning

system (such as a child or an adult seeking a movement solution in a novel task) (see Schöllhorn et al., 2006).

In summary, these four significant characteristics of nonlinear behavior, i.e., non-proportionality, multi-stability, parametric control and the functional role of noise, can inform learning design. They are important because they underpin the process by which learners as complex neurobiological systems can adapt to challenging performance environments. In the next section, we exemplify how these concepts can support a *nonlinear pedagogical* approach in the performance and learning context of sport, physical activity and exercise.

3. The role of constraints in facilitating motor learning: a basis for a nonlinear pedagogy

The conceptualization of humans as belonging to a class of nonlinear dynamical systems has logically led to the development of a nonlinear pedagogy (Chow et al., 2006; Renshaw, Chow, Davids, & Hammond, 2010). In nonlinear pedagogy, it has been argued that the process of learning can be guided by manipulation of key constraints that act on each individual (Davids, Button, & Bennett, 1999). From this perspective, different types of constraints can act as behavioral information to regulate action, functioning as system control parameters. To exemplify, a performance variable such as speed or force of movement, when systematically varied, might result in a change of learning system organization, illustrating how system parametric control may occur. This kind of control has been researched extensively in the *constraints-led framework* on motor learning (e.g., Araújo et al., 2004; Davids, Glazier, Araújo, & Bartlett, 2003; Davids et al., 2008). Newell (1986) classified constraints that parameterize learning dynamics as task, personal (i.e., organismic) and environmental. Task constraints in sport contain relevant information for learning a specific activity such as: rules of a game, certain contextual sources of information, performance areas and equipment, and number of individuals involved in the activity. On the other hand, personal constraints refer to the specific and unique characteristics of each learner which include: his/her morphological, psychological, physiological characteristics, for example. Finally, gravity, ambient light or temperature, as well as socio-cultural influences are some examples of environmental constraints which all learners have to satisfy to create performance solutions (see Chow et al., 2006 for a detailed review of the different categories of constraints).

These three classes of constraints do not influence the learning process independently, but rather form complex interacting configurations which shape the *perceptual-motor landscape* of the learner in specific directions (Kelso, Fink, DeLaplain, & Carson, 2001; Newell, 1996). The perceptual-motor landscape of a learner forms a hypothetical workspace where all potential movement solutions for an individual learner may exist. It is shaped by the interaction of the three main categories of constraints and forms the performance or learning context for each individual. In nonlinear neurobiological systems, constraint configurations do not prescribe each learner's behavior but simply guide it through interaction with his/her perceptual-motor systems.

The importance of the perceptual-motor system and how it uses information from the performance context is clearly exemplified by Jacobs and Michaels (2007) in their discussion on 'Direct Learning'. The lack of dependence on inference and cognitive processing as mechanisms for the acquisition of movement skills was highlighted. Instead, an emphasis on how information from the environment, in the form of ambient energy arrays, is considered critical in channeling learners to learn movement skills. Central to their discussion, Jacobs and Michaels (2007) illustrated learning as the process of change in the relevant informational parameters that informs action. Specifically, the learner's intentions and attention to these informational variables change when learning occurs (see Jacobs and Michaels (2007) for further discussion). This idea of 'Direct Learning', where perceptual information is directly mapped to action, is relevant to understanding how goal-directed behaviors emerge under the confluence of various constraints in the performance context. It is the presence of information rich arrays of energy in the performance context that guides action and the mapping of such higher order properties of ambient energy to action changes with learning.

It is, therefore, not surprising that the interaction of key constraints leads to individual differences in how learners assemble their unique movement solutions. This is an important advance since many traditional theories of learning recognize the existence of individual differences between learners, but fail to provide a comprehensive analysis of how such individual differences may be designed into learning programs. In contrast, a nonlinear pedagogical approach provides a principled, scientific framework for understanding individuality and applying the ideas in learning design (Davids et al., 2008; Phillips, Davids, Renshaw & Portus, 2010). Briefly, even if task and environmental constraints were considered as constant over some period, we can observe that the learning dynamics of each individual will be different since the interacting configurations of constraints will differ between learners. The distinctive configurations of constraints between learners are manifest in how each individual attempts to satisfy specific task constraints during practice. Hence, it is futile to try and identify a common, idealized motor pattern towards which all learners should aspire (e.g., learning a classical technique in a sport like tennis or cricket). This idea is prevalent in traditional approaches to motor learning and has tyrannized talent development programs for some time (Phillips et al., 2010). Different individual constraints suggest that it is dysfunctional to seek to establish universal optimal learning pathways to which all learners should adhere. Individual learners can often experience discontinuous, qualitative changes in their performance due to the presence of instabilities in their perceptual-motor landscape. For example, these instabilities may be due to growth, development, maturation and learning across the lifespan. While coaches or trainers might slowly vary the unique constraint configurations on each learner, the perceptual-motor landscape may undergo change of stable performance and learning pathways into unstable ones, requiring learners to quickly (i.e., on a much shorter time scale than the long term learning process itself) adapt to a newly emerged stable, movement solution. This

outcome is a product of the collaboration of three nonlinear properties: cause–effect non-proportionality, parametric (constraint) control and multi-stability in complex systems. In this way, nonlinear pedagogy frames the individuality of learning pathways and individuality of performance solutions for a given movement task. Additionally, it needs to be understood that constraints act on learning systems along different timescales, from the immediate (at the timescale of perception and action) to the more long term (at the timescale of developmental change over months and years). Throughout this paper we note how individual differences may substantiate the basis for a nonlinear pedagogy in which the goal of learners is not to re-produce an idealized movement pattern, but to assemble a personal, functional movement solution which satisfies the unique configuration of constraints impinging upon them at any instant in time.

Noise amplifies the exploratory activity of the learner and may guide him/her to discover individualized functional solutions to a specific task goal (Newell et al., 2008; Schöllhorn et al., 2006; Schöllhorn, Mayer-Kress, Newell, & Michelbrink, 2009). Intrinsic movement variability enlarges the area of solution search in the learner's phase space (i.e., the conceptual space of all possible movement solutions available for a specific learner as a complex system).

The positive role that noise plays is a feature of neurobiological learning in general. A study by Tumer and Brainard (2007) exemplified how other neurobiological systems (birds) can functionally adapt their behavior (bird singing) in the presence of 'noise'. Bird songs have been assumed to be highly stable, nearly "crystallized" forms of motor behavior once learned in a period of months. To test this assumption, a perturbation to a bird's auditory feedback was delivered in the form of short white noise burst sequences for higher pitch parts of the song. As a consequence of the perturbation, the birds immediately shifted the higher pitch syllables to avoid the sound and thus changed their song. The data showed that even highly stabilized forms of motor behavior can be changed in a preferred direction by application of stochastic perturbations to the system. This was an important finding for learning design theorists because it was observed in a form of neurobiological behavior which has been traditionally considered to be a stereotyped. This experiment demonstrated that noise in neurobiological systems has a functional role in producing subtle variations in well practiced skills with a consequence of producing highly adaptive patterns of behavior in ever-changing environments. The need for flexibility and adaptability was also demonstrated in recent work by Colunga and Smith (2008) who investigated how young children learn new words by leveraging on the stability of past experiences with the dynamic context of the present moment. Schöllhorn and colleagues have advocated a 'Differential Learning' approach, in which learners experience a variety of movement patterns (thus providing a 'noisy' learning environment), to encourage development of an individualized movement pattern that best fits the task dynamics of the performance context. In one study by Schöllhorn et al. (2006), on acquisition of dribbling and passing skills in soccer, participants were exposed to continuous changes in movement executions,

avoidance of repetitions, absence of corrective instructions and a focus on exploratory practice. This group outperformed other participants exposed to a traditional approach that emphasized repetition of an ideal movement technique. In summary, challenging individuals to perform different variations of a skill can be beneficial in engaging learners to search their perceptual-motor workspace for functional movement solutions by adding 'noise' in the form of movement variability to a target skill (see also Frank, Michelbrink, Beckmann, & Schöllhorn, 2008; Schöllhorn et al., 2009).

4. Meta-stability and self-organized criticality

Kauffmann's (1993) modeling of evolutionary processes resulting from spontaneous self-organization due to internal dynamics of a complex system provides most valuable insights for understanding neurobiological system dynamics during performance and learning.

He acknowledged how fluctuations in system stability reflect a general and essential principle of the pattern formation process in complex systems (see Bak, 1996; Bassingthwaighe, Leibovitch, & West, 1994; Camazine et al., 2003; Gisiger, 2001; West & Deering, 1995), including neurobiological systems (e.g., Gilden, 2001; Kelso, 1995; Van Orden et al., 2003). Many observations in science have shown that different kinds of physical, chemical, biological, psychological, and social systems all exhibit the same kind of fluctuations whose statistical character has proven to be puzzling and ubiquitous (Kello, Beltz, Holden, & Van Orden, 2007).

Research has shown how sometimes micro-level system fluctuations can lead to phase transitions so that new states of system order emerge. Kauffmann (1993) noted how phase transitions in system evolution are most prevalent in meta-stable regions of system state space in which co-evolving agents or components are poised between stability and instability. In this region they compete to modify system dynamics, a process known as co-adaptation. In neurobiological systems, co-adaptive behaviors can emerge out of fluctuations created by interactions between interdependent constituents of the system. Complex systems are most susceptible to fluctuations near their critical points (for reviews, see Bak, 1996; Solé & Goodwin, 2000; Sornette, 2004). When such self-organizing systems are poised in a critical state near this value, different types of behavior can emerge depending on the value of a system control parameter. Near the critical state, interactions between components and nearest neighbors can become correlated, in a type of domino effect, capturing global system interactions and leading to a sudden reduction from multiple options to one (a sudden collapse in the critical state). As we observe later, criticality actually provides the platform for a functional mix of creativity and constraint in dynamic performance and learning environments. It affords new opportunities for behavior which can fit newly arising circumstances of behavior. The connection between emergent interaction processes and neurobiological system fluctuations has its roots in Von Holst's (1939/1973) classic studies of coordination in a wide range of biological organisms. These studies identified two modes of neurobiological

coordination exemplified among anatomical components of fish. In one mode, each component (e.g., a fin) produced its preferred oscillatory pattern of activity regardless of the actions of other components. Von Holst (1939/1973) referred to this tendency towards independence of components as the *maintenance tendency*. Another mode was characterized by a tendency for components to produce in unison a single, common pattern of activity, referred to as the *magnet effect*. Importantly, neither mode by itself creates the coordination used for swimming in fish. Instead, locomotion is accomplished by a balance of these opposing modal tendencies that gave rise to what von Holst referred to as *relative coordination*, which stems from the weak meta-stable dynamics of the relative phase X (refer to Fig. 1). Von Holst's (1939/1973) work demonstrated how complex system components can work together to create a globally coherent pattern of activity, yet each component maintains its potential for independence. The balance of relative coordination allows system components to flexibly reorganize themselves into a variety of stable patterns of activity. Von Holst's (1939/1973) hypothesis of relative coordination has been elaborated to explain a wide variety of neurobiological system coordination including human movement patterns (e.g., Kelso & Clark, 1982; Rein, Davids, & Button, 2009; Schmidt, Beek, Treffner, & Turvey, 1991; Schwartz, Amazeen, & Turvey, 1995; Turvey, 1990).

Further exemplification can be observed in the analyses of performance in actual football matches (Mendes,

Malacarne, & Anteneodo, 2007) that show behavioral variables such as inter-touch times demonstrating a long-tailed q-gamma distribution (see Fig. 1b), that are characterized by highly intermittent dynamics. Parameters of these distributions signifying the average number of task phases forming complex compound tasks show that players' task solution dynamics dwell for a longer time around 2–3 sub-tasks. However, there are also extremely complex individual compound task solutions which contain more sub-tasks that need to be completed before a pass can be made to a team mate (as an example). The task solution space in football performance is meta-stable and by varying the task constraints of small-sided games, the coach may manipulate dynamic parameters of the system so that the system itself produces different frequencies of more simple, to very complex compound task solutions. Controlling such meta-stable dynamics through manipulating task constraints would enable learners to be embedded in varying representative contexts of their sport. Future research should focus on how the dynamics and, consequently, the probability distributions of such meta-stable systems change as a function of task manipulations.

4.1. Meta-stability in neurobiology

Relative coordination has since been replaced with the more general concept of *meta-stability* that originates from principles of thermodynamics. Meta-stability is

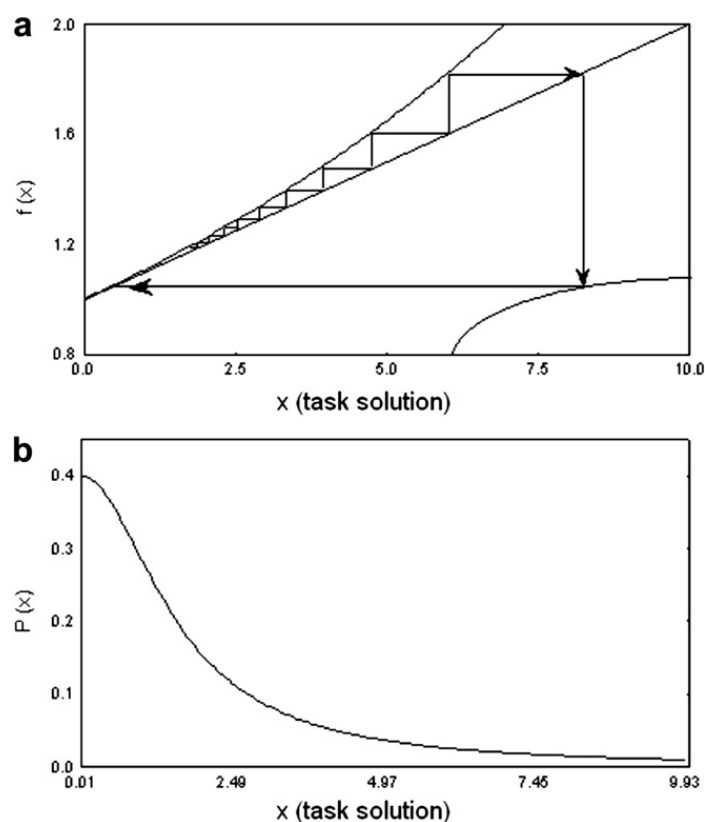


Fig. 1. An example of a meta-stable movement system of a weakly unstable type. a) A weakly unstable system. The task solution of the learner may dwell for some period close to some already acquired solution $x = 0$, but intermittently escapes and explores other available solutions. Such a situation provides the system the opportunity to be in a variety of stable patterns of activity. b) The probability $P(x)$ of learner's task solution x . It escapes from time to time away from the usual task solution $x = 0$ and explores other possible solutions.

characterized by ‘partially organized’ tendencies in which individual elements of a complex system (e.g., neurons, muscles, individuals in a group) are neither completely independent (local segregation), nor fully linked in a fixed mutual relationship (global integration). In a complex neurobiological system these characteristics can be observed near its *critical point* as the system shifts between ordered and disordered phases. A meta-stable regime in a neurobiological system is a state of organization between the idealized states of complete interdependence between interacting components (e.g., patterns of phase and frequency synchronization between regions of the brain or between body limb segments) and total independence of component parts from each other (e.g., each local region of the brain or limb segment expresses its own dynamic properties without interactions with other local regions or segments). Specifically, in the meta-stable regime of dynamically stable systems (refer to Fig. 1), intrinsic differences between individual components are of sufficient magnitude that they can ‘do their own thing’, while still retaining a tendency to cooperate. In this way global integration, in which component parts are locked together, is reconciled with the tendency of the parts to function as locally specialized autonomous units. Meta-stable coordination dynamics permit neurobiological systems to exhibit a far more variable, fluid form of organization, in which tendencies for integration and segregation coexist at the same time (Kelso, 2003).

In this region of system state space, a difference in circumstances that favors one behavioral option over another, no matter how slight, breaks the symmetry of equally poised options (Van Orden et al., 2003). The sand pile model developed by Bak, Tang, and Wiesenfeld (1988) described the existence of self-organizing criticality (SOC) in nature. These sudden and abrupt (i.e., catastrophic) transitions in system organization are due to self-organizing behaviors that evolve through dynamical interactions between system elements and are not driven by a peripheral agent.

In the study of cognition, Van Orden et al. (2003) showed how ‘criticality’ emerges from a fine balance between constraints on neurobiological systems. Criticality allows an attractive mix of creativity and stability as systems adapt to changes in dynamic performance environments. It creates new options for behavior and allows the choice of behavior to fit performance circumstances. An interesting issue for research on learning design is whether system criticality can be harnessed to facilitate the learning process. The ideas outlined here suggest that successful adaptations to environmental changes can emerge during learning without prescriptive interventions by an external agent. There is little need for an external agent, such as a manager, to fine tune in a highly prescriptive way the constraints of the learning environment.

However, under some sufficiently slow and subtle external drivers of a system during learning, i.e., brief instructions or modeling, rate of augmented feedback or an intrinsic change in a learner’s goal achievement, the configuration of constraints can self-organize and stabilize at the point which confines the system into a specific critical state. Many systems in nature exhibit this kind of dynamics (for elaborate examples, see Bak, 1996; Dhar, 2006), and this is a significant idea to understand in learning design. From this perspective, an important learning strategy could be to ensure that a learning system is deliberately channeled towards a critical state, where it can be exposed to fluctuations to induce emergent transitions in behavior.

There is some evidence from the performance context of team games to support this view, as we elucidate here. The hallmark of SOC dynamics is the power law distribution of a relevant variable (e.g., a movement state or its change) that captures the essence of the system’s behavior (see Fig. 2). The relevant variable could be the attacker–defender balance in team games. For example, defensive sub-systems usually have an advantage over attacking sub-systems typically during a soccer match. In such instances, we can observe that many actions emanating from the

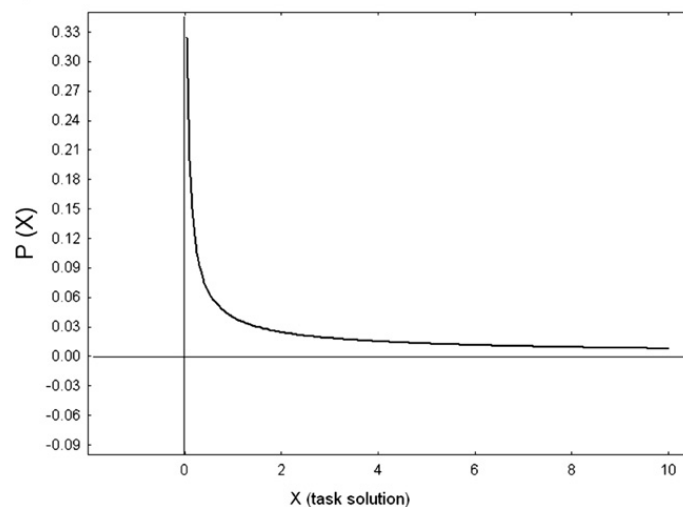


Fig. 2. Probability density functions of a meta-stable system of a self-organized criticality type. The figure shows a Power Law distribution and probability of emergence of a task solution. The usual task solution $x = 0$ is the most probable. However, the learner explores other solutions as well. The learner is posed stably in the critical region where spontaneous exploratory changes of different magnitude emerge.

attackers that only cause small disturbances in the defensive sub-system. However, an abrupt change in the attacker–defender balance occurs when a goal is scored. Nevertheless, it is common to observe many small disturbances of the attacker–defender balance, but very few abrupt disturbances that lead the attacking sub-system to score a goal (which may explain why football matches are usually low scoring!). This phenomenon can be captured with a power law distribution as displayed in Fig. 2, and self-organized criticality can be established as the underlying mechanism that explains this system property. It has also been observed that some variables evolving during performance of attackers and defenders in the team sport of rugby union possess a power law distribution, evidence for the presence of SOC in team games (Passos, Araújo, Davids, Milho, & Gouveia, 2009).

According to Bak's (1996) insights, it can be construed that, in the performance context of team games, most of the changes in the structural organization of a specific game can occur through catastrophic events. Team games are characterized by periods of stability that exist between intermittent bursts of activity and volatility (Passos et al., 2009). This intermittency in team games exemplifies the phenomenon of "punctuated equilibrium", a cornerstone of pattern forming dynamics of complex systems (Bak, 1996).

For example, in 1 v 1 sub-phases of team games, regardless of the many small fluctuations that may occur in the dynamics of the attacker–defender interactions, system stability can be abruptly broken rather than undergoing smooth gradual transitions. One moment a defender can be counterbalancing an attacker's actions, contributing to micro-system fluctuations, and the next moment the attacker can suddenly break this symmetrical organization, moving beyond the defender and creating space. In team games, attacker–defender systems evolve towards SOC regions without the direct design of an external agent (e.g., a coach). Rather attacker–defender dynamics emerge due to the influence of self-organization processes in team game pattern dynamics, a system property not possessed by any of its parts.

According to Kauffmann (1993, 1995), at this poised state between order and chaos (i.e., SOC regions), the unfolding consequences of actions on system components cannot be predicted. For this reason, in team games, SOC regions are shaped by the constraints imposed by local dynamical interactions rules amid agents in close proximity, such as teammates or opponents. In SOC regions, players' decisions and actions are ruled by a nonlinear contextual dependence amongst neighboring players which affords new opportunities for behavior fitting newly arising circumstances. To summarize, criticality provides the platform for a functional fusion of creativity and constraint in dynamic performance settings like team games. Undoubtedly, if learning designers can manipulate relevant task constraints to channel learners towards these SOC regions, the possibility of observing a myriad of different functional and creative, emergent actions will increase. Next, we exemplify the role of meta-stability and SOC in the acquisition of motor skills in sport and physical activity.

5. Meta-stability, criticality and skill acquisition

The arguments presented earlier highlighted how meta-stability is a functional system characteristic when learning to perform in complex, dynamic environments. This idea was neatly demonstrated by data from Hristovski, Davids, and Araújo (2009) in an experiment on boxers in an attacker–defender dyad. When scaling the frequency of an attacker's jab strikes and manipulating the affective constraints on both the attacker and defender, the defender was observed to exploit the enhanced variability of two modes of defensive action to create a new action combination. This strategy enriched each boxer's diversity (i.e., inter-mode variability) and the unpredictability of their actions. This newly created combinatorial mode proved to be highly adaptive in attaining the goal of the modified learning task, i.e., to gain performance points and win.

By manipulating the constraints of the learner and his/her environment, and increasing the amount of variability designed into the learning task, learners can be led to two different opportunities: a) finding a functionally optimal solution for a given class of movements in different sports (e.g., shot-puts in athletics, passes, dribbling, throwing in teams games etc.); and b), finding or creating new solutions or a new class of movements as a solution to a specific task goal. For this kind of meta-stability to be attained, learning designers must fine-tune task constraints to lead learners to the meta-stable state of the perceptual-motor landscape in the learning environment. The data of Hristovski et al. (2009) showed how, in the meta-stable state, learners can find it easier to assemble functional and novel movement solutions to satisfy the task constraints imposed on them during the process of learning. The hallmark of meta-stability and the type of exploration activity of the learner is a bi/multi-modal distribution function of the states of a relevant variable (see specifically Fig. 3c and d). Since the system is dynamically stable, variability needs to be enhanced so that transitions between the different movement states can be achieved. The variability in this type of meta-stability is generated by careful tuning of the task (e.g., punching frequency) and personal (e.g., affective) constraints. Thus, the magnitude of movement variability that is functional is *constraints dependent*.

The process of acquiring new movement skills can benefit from the presence of functional variability. For example, Chow, Davids, Button, and Rein (2008) demonstrated how successful participants learning a novel ball kicking task acquired new preferred movement patterns after a period of increased movement pattern variability. It is possible that the high variability in movement patterns, prior to the transition of a new preferred kicking pattern, emerged during a period of high system meta-stability when appropriate task constraints were established in a learning context (a suitable task goals to direct search for functional movement solutions that are individual-specific) (See Chow et al., 2008).

Other relevant research has been conducted in social performance contexts on groups in team sports. As noted earlier, Passos et al. investigated the behavior of attacker–defender dyads in rugby union discovering that it was ruled by a power law distribution as in Fig. 2 (Passos et al., 2009).

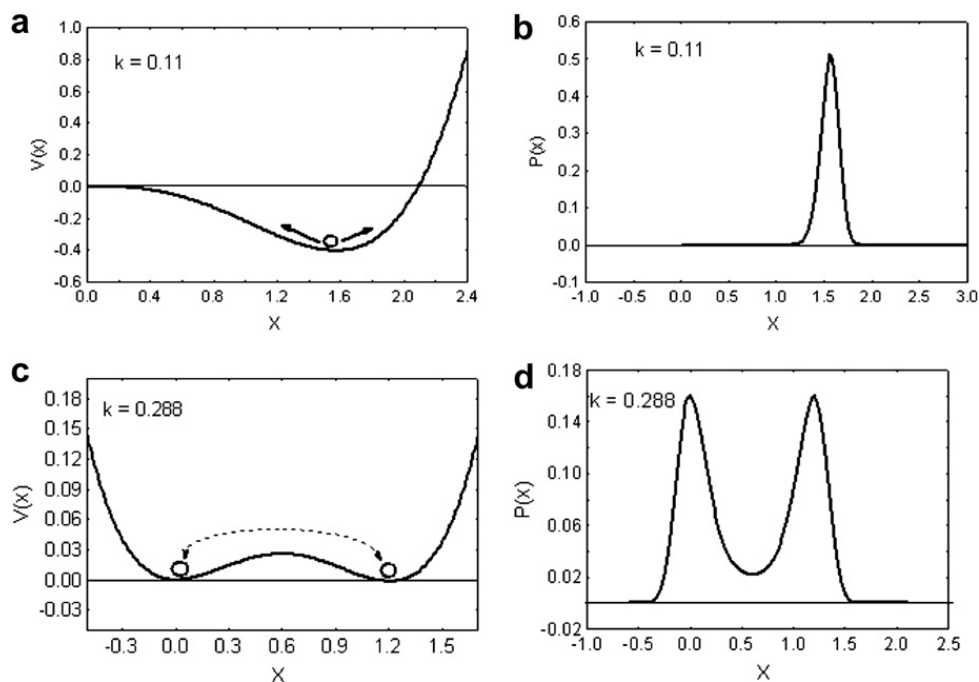


Fig. 3. Examples of various states in systems with meta-stability of a weakly stable type. a) An example of stable movement dynamics. For a control parameter value $k = 0.11$ the movement system resides in the attractor, i.e., task solution $x = 1.57$. The intrinsic noise makes the system fluctuate close to that state (represented by arrows). b) For the same value of the control parameter the probability of finding the learning system in another state other than $x = 1.57$ is low. The system explores only a tiny portion of the possible task solutions. c) An example of a meta-stable state of a weakly stable kind. As the control parameter, i.e., a constraint, is varied and attains value $k = 0.288$, there are already two weakly stable degenerate (i.e., equal minima) states. As a consequence of intrinsic noise and the system's weak stability, it switches interchangeably into two modes $x = 0$ and $x = 1.2$ (represented by dashed arrow). The task solution $x = 0.6$ is an absolutely unstable point that repels the system towards one of the weakly stable states. d) In this situation, the movement system explores a much wider area of the possible states as exemplified by the area occupied by the probability density function. It is important to note that both the control parameters (constraints) manipulation and the noise cooperate in system's dynamics, resulting in stability or meta-stability for the system.

This finding signified that dyadic (i.e., attacker v defender) system behavior in team sports evolves throughout SOC regions poised at the edge of chaos, where the players were equally likely to act independently and inter-dependently in performance. In this region of criticality, it was clear that players' decisions and actions are governed by local emergent interactions rules rather than *a priori* instructions provided by external agents (such as coaches, teachers, parents, significant others). These insights provide some relevant consequences for learning design in group training contexts like team sports, when considered as complex systems. Too much prescriptive advice on decision making and action should be avoided in practice, for example, when individual performers are encouraged to undertake drills during training. Over-emphasizing prescription might lead learners to highly stable behaviors (i.e., deep attractors that are robust to external perturbations), decreasing the ability to adapt to dynamic performance environments. These findings verified how learning environments should be designed in a nonlinear pedagogy. Submitting learners to this sort of learning design philosophy increases their attunement to relevant information constraints, as well as allowing them to calibrate their movements to key informational variables, leading them to a range of functional decisions and actions (Araújo, Davids, Chow, & Passos, 2009).

Like training in individual activities, an important pedagogical strategy in group training is to channel learners to SOC regions, where systems may be poised for

a transition. In these regions, successful learning can occur as individuals seek to adapt to dynamic environmental constraints (Davids et al., 2008; Renshaw et al., 2009). Through task constraints manipulation, it is feasible to create learning environments with constraints that are representative of those that players will face during performance (e.g., small-sided games) (Renshaw et al., 2010). This approach to learning design in team games drives individuals towards SOC regions that emerge during attacker-defender interactions in the game. For example, recent work conducted with the Australian Women's Water Polo Team at the Australian Institute of Sport provides a practical insight to understand how the effective manipulation of task constraints can lead performers towards SOC regions (see Chow et al., 2009). This directing of search involved, for example, the use of huge Swiss balls to occlude vision while taking shots, the use of rubber tubing for perturbing players' body and arms during shooting practices in small-sided-games, and the use of various modified equipment (e.g., different weighted balls for passes and reception). The need to change individual constraints (e.g., to develop technical skills) can also emerge when performers cannot adapt to continuously changing environmental conditions (e.g., respond to a perturbation provided by an opponent). In these learning situations, coaches or trainers need to develop representative task designs through task constraints manipulation (e.g., adding or changing new rules; increasing or decreasing field dimensions; modifying equipment). A task representative

of the context towards which one intends to generalize, is one where the information is diagnostic, to allow attuned players to detect and use the informational variables that guide them to the task goal (Araújo, Davids, & Passos, 2007; Araújo, Davids, & Serpa, 2005). A change in constraints can act as a catalyst for new movement patterns to emerge by helping to induce more functional variability in the learner.

To summarize, task constraints manipulations can drive learning systems towards a SOC region poised for a transition. In this region of system phase space, new coordination patterns and actions are more likely to emerge which enhance the learners' attunement to sensitive information available in a performance context.

6. The role of noise in learning environments

As noted earlier, the introduction of noise, in the form of random variability, to a system can allow exploratory behaviors to surface and is critical for movement behaviors to transit from one pattern to a new adaptive pattern during learning (Kelso, 1995; Liu, Mayer-Kress, & Newell, 2006; Riley & Turvey, 2002). While it has been recognized that not all noise is necessarily beneficial, (Hamill, Haddad, Heiderscheit, Emmerik, & Li, 2006) a key challenge is to strategically design noise into a learning task to encourage functional and adaptive learning.

Colored (i.e., correlated) noise has structure to it and, from a learning perspective, the manipulation of constraints (especially task constraints) provides movement variability that is constrained to a restricted range in the motor system degrees of freedom needed by the learner. The term 'colored noise' comes from the analogy with properties of light in physics. Noise is white when all its components can equally contribute to the overall power of the noise, as in white light where different colors contribute equally to the spectrum. Colored noise, on the other hand, is a type of noise in which some, usually lower frequency (e.g., red) components, contribute more than others, and their relation is exactly or approximately that of a power law type. In the light analogy, the implication is that added noise to learning environments should not be white, but pink or red. For example, note that lower values of X states in Figs. 1 and 2 are dominant when compared to high X values and their relation is approximately (Fig. 1), and exactly (Fig. 2), of a power law type. So, the variability of those processes is colored.

The inclusion of colored noise in a learning environment will act as a constraint to perturb the learner to meta-stable regions of the perceptual-motor performance workspace. In this region a learning system will be poised at the edge of instability to facilitate possible transitions between movement behaviors that could be dynamically effective for constantly changing performance situations. This potential was demonstrated in a study by Hristovski, Davids, Araújo and Button (2006) who investigated the impact of manipulating target distance on boxing action patterns of novice boxers. Distance between boxers and a punching bag was varied and it was found that different scaled-body distances afforded the emergence of different boxing patterns (e.g., hooks, jabs, uppercuts). Interestingly, at

a critical scaled-body distance (0.6), boxers were in a maximal meta-stability state where they could flexibly switch between any of the boxing action modes. It seemed that the scaled-body distance value of 0.6 was critical in pushing the boxer movement system to the edge of instability, from where each punching mode could be spontaneously activated under the task and the perceived environmental constraints (Hristovski, Davids, & Araújo, 2006; Hristovski, Davids, Araújo, et al., 2006). At other values of scaled distance this level of flexibility in emergent actions was not observed.

The promotion of discovery-type pedagogical approaches in recent decades has prompted increased discussion on effectiveness of these approaches for improving learning. Such 'divergent discovery learning' approaches (e.g., Teaching Games for Understanding or Game Sense pedagogical approaches in Physical Education) emphasize the design and delivery of learning activities in a structured way so that learning is guided, as learners seek functional movement solutions within a restricted workspace of effective behaviors. Clearly, in performance contexts such as mountain climbing or kayaking, discovery learning based on random variability may not have desirable consequences for learners. In these circumstances, the difference between random fluctuations and colored fluctuations in learning systems needs to be recognized in learning design to ensure that the type of noise utilized is functional to meet the goal of the learning environment. That is, variability infused in learning design needs to be constrained, as we explain below.

The coupling that emerges between a learner and the dynamic performance environment in team games during learning implies that it is important to discern the type of dynamics induced by the co-adaptive movements of attackers and defenders. The dynamics in such learning environments are typically complex and stochastic, with the perception-action dynamics in different settings and tasks demonstrating different types of variability (random or correlated (colored) noise). Different types of environmental information variability could have profound effects on the success of finding new solutions to task goals set during learning. In other sciences it has been shown that, correlated (colored) noise can enhance the switching rate between stable specific modes of behavior more successfully than uncorrelated (white) noise (Wio, 2005).

The implication of these data for learning designers is to determine how constraints can be manipulated to channel learners towards a meta-stable state where different movement solutions are available for them to explore. Performing in such a meta-stable state would lead to high levels of movement variability, with lots of 'noise' in the learning system. However, with specific manipulations of task constraints, the 'noise' type can be structured. In this way only 'selected' movement solutions will be available to learners as a consequence of the confluence of constraints for the practice environment. It is a challenge for learning designers to find the right balance to ensure that the task constraints are not too tight so that the meta-stable region is too small, with very little 'room' for exploring functional movement behaviors.

These findings illustrate why more recently there has been much greater emphasis in exploring how noise can be

infused in the motor learning process, exemplified by studies of varying levels of stochastic perturbations present with different learning approaches (see Schöllhorn et al., 2009). From this work, it seems that there are implications for varying the movement solution options for different skill levels of learners. These ideas suggest that more options need to be created for advanced learners and fewer options for novice learners, seeking to establish stable movement patterns, when designing practice tasks. This strategy would infuse a relevant amount and type of noise to place learners in the meta-stable region of a complex system, with an emphasis on individual differences in learning.

The role of noise was also highlighted in research work on acquisition of cognitive knowledge. Kapur (2008) investigated the role of 'Productive Failure' to determine the impact of differentiated structured questions relating to Newtonian kinematics on learning. The concept proposed by Kapur (2008) is similar to the ideas proposed by Bjork et al. (1994, 1999) on 'desirable difficulty' where learners experience greater performance errors during learning, but are more successful in retaining knowledge and information eventually. Kapur (2008) observed that, while participants presented with ill-structured questions experienced greater initial failure through discussions that were divergent and complex, these same students actually outperformed students in a 'well-structured' question group on both ill-structured and well-structured problems at post-test. It seemed that the 'noisy' structure for participants presented with ill-structured problems allowed them to engage in complex analytical discourse that actually yielded a richer, more meaningful and stable understanding of the content. From the perspective of functional variability, it is possible that participants from the ill-structured group could have been searching a larger phase space of available cognitive solutions for the cognitive task at hand. More interestingly, Kapur (2008) suggested that one of the strengths of a 'productive failure' approach was that some form of structure could indeed be present for participants in the ill-structured group (although not in an organized and explicit format), that emerged from within rather than due to the influence of an outside agent (a teacher for example). This observation is harmonious with explanations of how emergence of action could surface and be self-organized as a consequence of the interaction among system components, rather than as a result of an over-arching external authority.

During motor skill learning when noise can be incorporated, free competition between solutions will exist, and coaches or trainers do not risk being too prescriptive in directing learners in acquiring decision-making skills. Such insights can provide impetus for further empirical work on the role of noise in designing appropriate learning contexts for meta-stable regions to surface.

7. Motivation to learn as a pre-requisite

It is also worth briefly highlighting that one of the key pre-requisites to be considered for learning to occur is a fundamental personal constraint: willingness of individuals to learn. The need to infuse appropriate elements in

learning design to encourage motivated learners has to be considered. How do we get learners ready to learn? Langan-Fox, Armstrong, Balin, and Anglim (2002) clearly articulated that setting appropriate task goals and providing relevant incentives can strongly encourage relevant processes concomitant to effective skill acquisition. It seems that setting specific and challenging task goals are key pedagogical constraints that can encourage learners to acquire goal directed behaviors. Moreover, a self-directed learning climate could also aid in increasing motivational level for learners even at the initial stage of learning motor skills (Martin, Rudisill, & Hastie, 2009).

This is clearly relevant to a nonlinear pedagogical approach where appropriate task goals provide a platform for learners to independently search and explore functional movement behaviors. Establishing relevant task goals pegged to appropriate learning stages of learners can help to motivate learners to learn more effectively. For example, if a learner is at the Control stage of learning (see Newell, 1985 for a description on learning stages) where he/she is able to flexibly adapt a stable movement pattern to approximately fit changing performance environments, task goals that requires him/her to, for example, play a tennis ground stroke to different positions in the court (varying accuracy and weighting of strokes) will be appropriate to increase motivation to learn.

8. Conclusions

In this paper, we have highlighted how, in complex neurobiological systems, behavioral changes can occur as a consequence of the interplay of constraints in the learning environment. A key task in learning design is to manipulate system constraints to guide exploration and discovery of functional movement solutions. Understanding the significance of concepts like meta-stability, self-organizing processes in critical states of a learner's system, and the influential role of 'noise' in the learning environment, can inform understanding of learning design. The strategy of manipulating key task, personal and environmental constraints can harness self-organizing processes in the meta-stable region of the learning system. In the meta-stable region, learners can creatively and flexibly use different functional behaviors, depending on the design of the practice task constraints. In this region of system phase space, learners can exploit inherent multi-stability to assemble different movement solutions in achieving task goals. Harnessing multi-stability provides the basis of adaptive behaviors. Task constraint manipulation can drive learners towards a SOC region where they can be poised for a transition in performance. In this region of system phase space, new actions and performance solutions can emerge which enhance learners' attunement to sensitive information available in a performance context.

These ideas based on contributions from psychology, biology and physics form a multidisciplinary basis of a nonlinear pedagogical approach that encompasses learning in a situated setting where no single component in a system has over-riding control of emergent behavior. Further research is required as concepts emanating from Nonlinear Pedagogy are continuously refined and

developed to create a systems-based approach to learning design.

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