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Nonlinear Dynamical Systems for Theory And Research In Ergonomics

Stephen J. Guastello
Marquette University, stephen.guastello@marquette.edu

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Stephen J. Guastello
Department of Psychology, Marquette University, Milwaukee, WI

Abstract

Nonlinear dynamical systems (NDS) theory offers new constructs, methods and explanations for phenomena that have in turn produced new paradigms of thinking within several disciplines of the behavioural sciences. This article explores the recent developments of NDS as a paradigm in ergonomics. The exposition includes its basic axioms, the primary constructs from elementary dynamics and so-called complexity theory, an overview of its methods, and growing areas of application within ergonomics. The applications considered here include: psychophysics, iconic displays, control theory, cognitive workload and fatigue, occupational accidents, resilience of systems, team coordination and synchronisation in systems. Although these applications make use of different subsets of NDS constructs, several of them share the general principles of the complex adaptive system.

Practitioner Summary: Nonlinear dynamical systems theory reframes problems in ergonomics that involve complex systems as they change over time. The leading applications to date include psychophysics, control theory, cognitive workload and fatigue, biomechanics, occupational accidents, resilience of systems, team coordination and synchronisation of system components.

Keywords:
General ergonomics, application domains, team working, organisational ergonomics, mental fatigue, psychological aspects, learning and skill acquisition, psychological aspects, operator workload, system performance

1. Introduction
The growing complexity of sociotechnical systems has produced a need for a paradigm shift in the scientific development and practice of ergonomics (Karwowski 2012; Walker et al. 2010), as it has done across the range of social and life sciences (Allan and Varga 2007; Dore and Rosser 2007; Fleener and Merritt 2007; Guastello and Bond 2007; Ibanez 2007; Zausner 2007). A new scientific paradigm would produce new concepts for understanding phenomena, new questions to be asked, new methods to accompany the new questions and new explanations to be offered for phenomena. It would also improve on extant explanations for phenomena that might have been fragmented or elusive altogether by changing a perspective in a significant way. The next sections of this article expand on NDS' axioms, historical origins, core constructs, methodologies and some of its developing application areas in ergonomics. In each case, it is necessary to be concise so as not to lose the big picture of the transformation that is taking place.

1.1. Axioms
Nonlinear dynamical system (NDS) has four features that should be considered axiomatic. First, simple deterministic functions can produce events that are apparently random; identifying the function can be challenging. The analysis of variability is at least as important as the analysis of means, which pervades the linear paradigm. Unlike the analysis of variance and the twenty-first century developments thereto, NDS is concerned with the amount and structure of the variability, the underlying processes that produce those patterns of variability, and the identification of system variables that could influence the outcomes within those structures.

Second, there are many types of change that systems can produce, not just one simple type of generic change. They are represented by numerous modelling structures such as attractors, bifurcations, chaos, fractals, catastrophes, entropy, self-organisation, emergence and synchronisation (Guastello and Liebovitch 2009; Sprott 2003). Temporal patterns are essentially the footprints of particular underlying dynamics. Except in rare circumstances time is an implicit variable, not an explicit independent variable. Instead, the core functions are framed such that a state of an agent at time-2 is a nonlinear function of the agent's state at time-1 and other influences from control variables; see the fourth axiom below.

Third, contrary to common belief, systems are not simply waiting in a state of equilibrium until they are perturbed by some force from outside the system. Rather, stabilities, instability and other change dynamics are produced by the system as it behaves 'normally'. This is not to say that perturbations or random shocks cannot originate outside the system. Indeed they can do so, and perturbations can arise from inside the system as well. The researcher would then look for *control variables* that govern the reactivity of the system to perturbations.

Fourth, the concept of causality changes to concepts of *control* and *emergence*. In the more traditional thinking, Event A that occurs today causes Event B tomorrow. If A did not happen, neither would B, and that would be the end of the possible outcomes. In NDS, each agent is following a dynamic path that is strongly influenced by its previous state. Other variables and external events can deflect or redirect the path of the agent, either by a little or a lot. The effect of such variables is dependent on the previous state of the agent or system; small influences can produce large results and large influences can produce nothing at all, depending on the prior state of the agent or system. Furthermore, not all control variables play the same role in the dynamics.

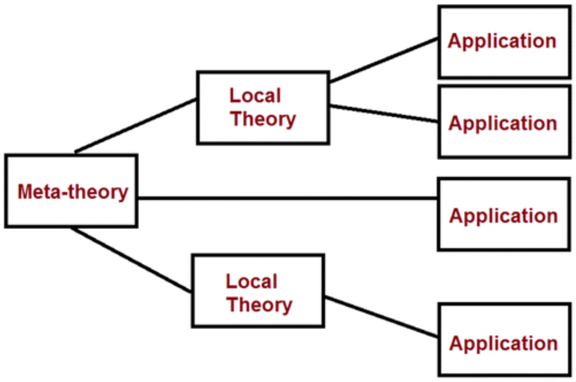
Many problems that need to be solved, either in a theoretical or pragmatic context, cannot be reduced to single underlying causes. Rather, they are emergent products of complex system behaviours and internal interactions. Emergent phenomena involve both bottom-up and top-down processes. Although they often appear to 'come out of nowhere', there are known processes by which they can occur; one just needs to view a situation through the right lens. The new forms of research questions that proceed from the foregoing axioms bring about a need to develop appropriate research methods to answer those questions.

1.2. Historical roots

NDS is a general systems theory in the sense that its principles and models have found applications to a wide range of phenomena that might have appeared unrelated at first blush until their common intrinsic dynamics were discovered. It has made good use of some general systems concepts from the 1950s such as feedback loops and mathematical formalisms as the core elements of its applications (Guastello and Liebovitch 2009). NDS' primary origin was differential topology, and over the years the connections among its contributing constructs have grown. Although many of the ideas were developed in the context of problems in physics, any isomorphism between phenomena in physics and those of the life sciences reside in the mathematics, not in any necessary assumptions about physical processes. Nonetheless, good analogies often pay off well.

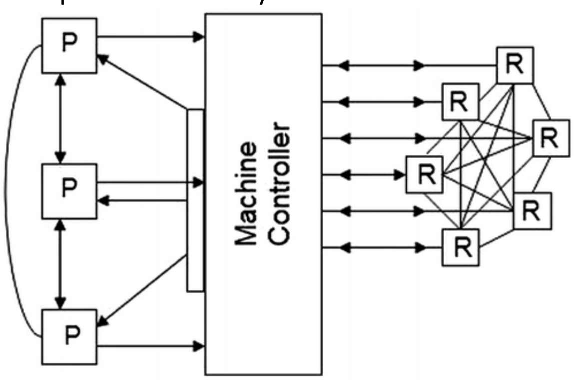
When NDS principles combine with the theoretical constructs within a particular application, they play the role of a meta-theory: Broad theoretical principles guide the organisation of constructs within the local theory, which in turn shapes the approach to studying a local phenomenon (Figure 1). There could be occasions where a phenomenon needs investigating, but a local theory has not been previously defined. Here, the meta-theory could shape the development of both.

Figure 1. The hierarchical relationships among meta-theory, local theories, and applications.



Ergonomics has made productive use of systems thinking. The person–machine system is perhaps the most obvious systems idea (Meister 1977). The nature of the system has expanded in scope to include the immediate workspace, less immediate environments where related subsystems can reside, and multiple integrated person–machine systems, or swarming robot configurations (Figure 2). Teams, group dynamics and communications are have also risen in importance (Cooke, Duchon, et al. 2012; Gorman, Cooke, and Salas 2010).

Figure 2. Configuration for the operation of swarming robots. Source: Reprinted from Guastello (2014a, 376) with permission of Taylor and Francis.



Applications of NDS in ergonomics first appeared in the 1980s, starting with shift work and industrial production, physical workload, fatigue and occupational accidents (Guastello 1982, 1985, 1988; Guastello and McGee 1987). A broader state-of-the-science compendium of psychological applications today would include neuroscience; psychophysics, sensation, perception and cognition; motivation and emotion, group dynamics, leadership, and collective intelligence; developmental, abnormal psychology and psychotherapy; and organisational behaviour and social networks (Dishion 2012; Dooley, Kiel, and Dietz 2013; Guastello 2009a; Guastello, Koopmans, and Pincus 2009); psychomotor coordination and control (Shelhamer 2009); creativity (Guastello and Fleener 2011), education (Stamovlasis and Koopmans 2014) and medical practice (Katerndahl 2010; Sturmberg and Martin 2013).

2. Primary NDS constructs

2.1. Attractors and bifurcations

The structures previously known as 'equilibria' are now understood as one of several basic forms of attractor. An attractor is a piece of space. When an object enters, it does not exist unless a substantial force is applied to it. The simplest attractor is the *fixed point*.

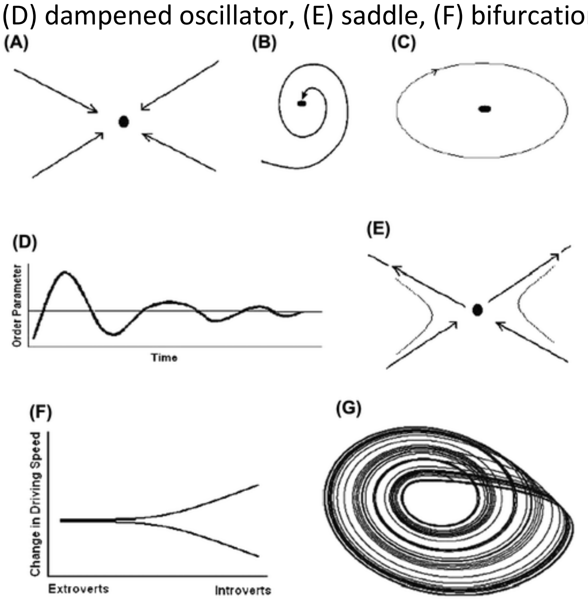
Oscillators, also known as *limit cycles*, are another type of attractor. They can be simple oscillators, dampened to a fixed point by means of a *control parameter*, or perturbed in the opposite direction to become *aperiodic oscillators*. There is a gradual transition from aperiodic attractors to chaos.

Repellors are the opposite of attractors. Objects that veer too close to them are pushed outwards and can go anywhere. This property of an indeterminable final outcome is what makes repellors unstable. Fixed points and oscillators, in contrast, are stable. Chaotic attractors (described below) are also stable in spite of their popular association with unpredictability.

A *saddle* has mixed properties of an attractor and a repellor. Objects are drawn to it, but are pushed away once they arrived. A saddle is also unstable.

Bifurcations are splits in a dynamic field that can occur when an attractor changes from one type to another, or where different dynamics are occurring in juxtaposing pieces of space. Bifurcations can be as simple as a single point, or they may involve trajectories and patterns of instability that can become very complex. The example in Figure 3 is one of the simpler forms of bifurcation. This example from Cobb (1981) and (Zeeman 1977) shows the effect of alcohol on driving speed in a simulator. Extroverts maintain speed, whereas introverts show substantial changes in both directions. Very few observations fall within the space between the two curves.

Figure 3. Gallery of elementary dynamics: (A) fixed point, (B) fixed point, spiral type, (C) oscillator or limit cycle, (D) dampened oscillator, (E) saddle, (F) bifurcation, (G) top-down view of the Rossler chaotic attractor.



2.2. Chaos and fractals

The essence of *chaos* is that seemingly random events can actually be explained by simple deterministic processes or equations (Kaplan and Glass 1995; Sprott 2003). Chaos has three hallmark properties: sensitivity to initial conditions, boundedness and unpredictability.

Sensitivity to initial conditions means that two points can start by being arbitrarily close together, but as the same function continues to iterate for both of them, the two points become increasingly farther apart; this is the well-known *butterfly effect* (Dooley 2009; Lorenz 1963). *Boundedness* means that, in spite of any volatility, the values of the measurement stay within a fixed range. *Unpredictability* is actually a matter of degree and sometimes an overstatement, depending on the context. What actually occurs is that it the predictability of a point from a previous one decays as the time interval becomes larger (Smith 2007). The ability to predict points changes in our favour if we know the nonlinear function in advance, which is seldom the case in ergonomics at the present time.

The basin, or outer rim, of a chaotic attractor has a fractal shape. A *fractal* is a geometric structure that has non-integer dimensionality and self-repeats as one zooms in or out from a target image. When viewed in their abstract forms, it is possible to see the entire fractal image at larger and smaller levels of scale. Although they have strong aesthetic appeal (Sprott 2004), the aesthetic properties of fractals are not particularly useful for ergonomics research. Fractal *structure,* however, can be analysed to interpret the ruggedness of a landscape (Mandelbrot 1983), the complexity of a time series (Guastello and Gregson 2011; Mandelbrot 1999), or the distribution of the sizes of events or objects after a self-organising process has taken place (Bak 1996). For this purpose, we would compute the *fractal dimension* of a time series of behavioural observations and examine how it varies across situations or from the individual, group or greater collective levels of analysis.

Fractal dimensions close to 0 denote fixed points. Dimensions around 1.0 indicate either a line or a perfect oscillator. Dimensions between 1 and 2 are in the *zone of self-organised criticality* (SOC), in which a system adopts a lower entropy structure after having been in a state of chaos, or far-from-equilibrium conditions for some time previously. In living systems, it reflects a healthy balance between the variability needed to make an adaptive response with the least amount of effort.

Levi flights are bursts of behaviour in an unexpected direction after the system has spent most of its time in a relatively steady state; they tend to occupy dimension ranges between 2 and 3. Chaos is usually associated with dimensions of 3.0 or more (Nicolis and Prigogine 1989), but there are some well-known chaotic attractors that have fractal dimensions less than 3.0.

2.3. Information and entropy

The entropy construct underwent some important developments since it was introduced in the late nineteenth century. Initially, it meant ‘heat loss’. This definition led to the principle that systems will eventually dissipate heat and expire from ‘heat death’. A century later, this generalisation turned out to be incorrect, when it was discovered that systems respond to high entropy conditions by self-organising (Haken 1984; Prigogine and Stengers 1984) in a way that establishes a low-entropy state.

The second perspective originated in the early twentieth century with statistical physics. It was not possible to target the location of individual molecules, but it was possible to define metrics of the average motion of the molecules. Shannon entropy was the third perspective: A system can take on any number of discrete states over time. It takes *information* to predict those states, and any variability for which information is not available to predict is considered entropy. Entropy and information add up to H_{MAX}, maximum information, which occurs when all the states of a system have equal probabilities of occurrence:

$$H_s = \sum_i [p_i \log_2(1/p_i)]$$

(1)

where *i* is a system state and *p* is the probability of that state (Shannon 1948).

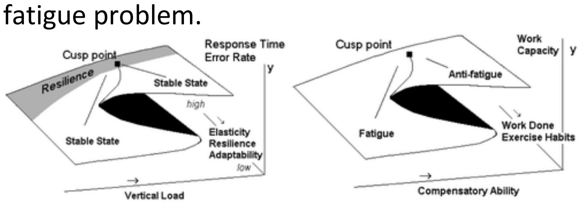
The NDS perspective on entropy, however, is that entropy is generated *by* a system as it changes behaviour over time (Nicolis and Prigogine 1989; Prigogine and Stengers 1984) and thus it has become commonplace to treat Shannon information and Shannon entropy as interchangeable quantities. Other computations of entropy have been developed for different types of NDS problems (Guastello and Gregson 2011).

2.4. Catastrophe models

Catastrophes are sudden changes in events; they are not necessarily bad or unwanted events as the word ‘catastrophe’ might suggest in English. Catastrophes involve combinations of attractors and bifurcations, and are operating in some self-organising events. According to the classification theorem (Thom 1975), all discontinuous changes of events can be described by seven elementary topological models. The models are hierarchical such that the simpler ones are embedded in the larger ones.

The *cusp* model (Figure 4) is the second-simplest in the series – just complex enough to be very interesting, unique and useful. There are two control parameters, *asymmetry* and *bifurcation*. To visualise the dynamics, start at the stable state on the left and follow the outer rim of the surface where bifurcation is high. If we change the value of the asymmetry parameter, nothing happens until it reaches a critical point, at which we have a sudden change in behaviour: The *control point*, which indicates what behaviour is operating, flips to the upper sheet of the surface. A mirror image process occurs when shifting from the upper to the lower stable state. Notice that the upward and downward paths occur around different thresholds.

Figure 4. The cusp catastrophe response surface. These examples are labelled for the cognitive workload and fatigue problem.



When the bifurcation effect is large, the discontinuous dynamics of the outer rim of the surface occur. When the bifurcation effect is low, change is relatively smooth. The darkened area between the stable states (attractors) is an area where few data points are likely to land, because a repellor is located there. The cusp point (a saddle) is the most instable location on the surface. The paths drawn between the cusp point and the stable states are *gradients*. Cusp models have been informative for problems involving cognitive workload and fatigue, biomechanics, and accident analysis and prevention; those applications are expanded further in Sections 4.3, 4.5, and 4.8.

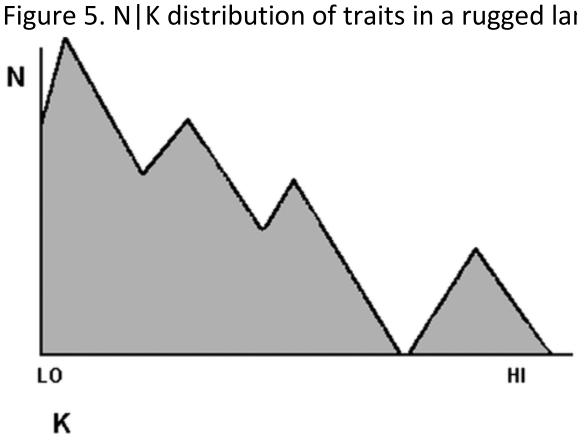
2.5. Self-organisation and emergence

The group of NDS constructs that is often known as 'complexity theory' is concerned with self-organising phenomena and the effect of one subsystem behaviour on another. Self-organisation is sometimes known as 'order for free' because systems acquire patterns of behaviour without any input from outside sources. Three distinct models of self-organisation are considered next: the rugged landscape, (Kauffman 1993, 1995); the sand pile (Bak 1996); and synergetics (Haken 1984). The principle that they share is that systems self-organise in response to the flow of information from one subsystem to another.

For the *rugged landscape* scenario, imagine that a species of organism (or generic *agent*) is located on the top of a mountain in a comfortable ecological niche. The organisms have numerous individual differences in traits that are not relevant to survival. Then one day something happens and the organisms need to leave their old niche and find new ones on the rugged landscape, so they do. In some niches, they only need one or two traits to function effectively. For other possible niches, they need several traits. There will be more organisms living in a new 1-trait environment, not as many in a 2-trait environment, and so on.

Figure 5 is a distribution of *K*, the number of traits required, and *N* the number of organisms exhibiting that many traits in the new environment. Notice, however, that there is a niche towards the right side of the distribution that looks more populated than its lower-*K* neighbours. A simple rule that predicts when clusters like these will occur has not been officially determined yet, but there is reason to suspect that it results from interactions among heterogeneous agents within the niche.

Figure 5. N|K distribution of traits in a rugged landscape.



Kauffman's third parameter is *C*, complexity of interaction. A landscape is rugged to the extent that that the interactions among agents within a niche are frequent and varied in nature. If the interaction level is high, it becomes more difficult for new agents to assimilate into the niche.

Vidgen and Bull (2011) introduced two more parameters of complexity to the rugged landscape: *S*, the number of interacting species of agent, and *R*, the differential rates of change for the different species.

Interactions among agents eventually produce change in the agents' behaviour and cognitive schemata. As a result they co-evolve. The antics of one species set the stage for the evolution of the others. They amplify each other's variation through interaction. Ergonomically, what we can observe is that person–machine systems morph as they interact with other systems. The rates of change for the interacting agents can be very different, and these differences alone can produce substantial variability in the final outcomes of all the interactions (Guastello, Reiter, and Malon 2015; Matsumoto and Szidarovszky 2014).

For Bak's (1996) sand pile and avalanche model, imagine that we have a pile of sand, and new sand is slowly drizzled on top the pile. At first nothing happens, but suddenly the pile avalanches into distribution large and small piles. Importantly, the frequency distribution of large and small piles follows a *power law distribution*. A power law distribution is defined as

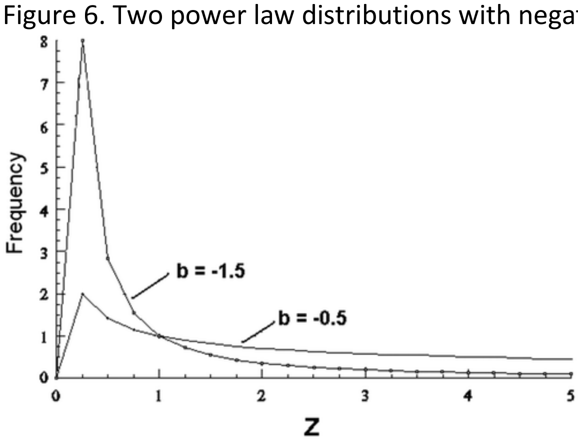
$$\mathrm{FREQ[X]} = aX^b$$

(2)

where *X* is the variable of interest (pile size), *a* is a scaling parameter and *b* is a shape parameter.

Different shapes are produced when *b* is negative versus positive. The distributions with negative *b* are of greater interest in NDS, however. Two examples appear in Figure 6. When *b* becomes more severely negative, the long tail of the distribution drops more sharply to the X axis. Self-organising phenomena of interest contain negative values of *b*. The $|b|$ is the fractal dimension for the process that presumably produced them. The widespread reports of the $1/f^b$ relationships led to the interpretation of fractal dimensions between 1.0 and 2.0 as being the *range of SOC*.

Figure 6. Two power law distributions with negative shape parameters.



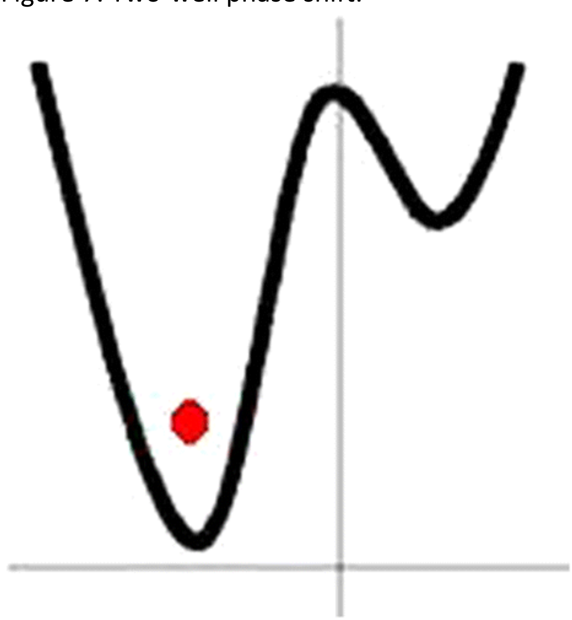
Synergetics captures two further aspects of self-organising systems. One is that the connections that occur between subsystems can have different temporal dynamics. For instance, if a chaotic *driver* feeds information to a periodic *slave,* the slave will, as a result, produce aperiodic output. This is just one simple example of analysing a system for driver–slave dynamics that are potentially complicated.

A second theme from synergetics is the phase shift that a system undergoes when it changes from one configuration of connections to another. For instance, a person might be experiencing a medical or psychological pathology that is unfortunately stable and prone to continue until there is an intervention. The intervention takes some time and effort, but the system eventually breaks up its old form of organisation and adopts a new one (Heinzel, Tominschek, and Schiepek 2014; Leining, Strunk, and Mittlestadt 2013). This is also the phase shift form of emergence (Goldstein 2011). Many examples of phase shifts have been reported across disciplinary areas. The change in the system is akin to water turning to ice or to vapour, or vice versa. The challenge is to predict when the change will occur, which is what researchers who follow the synergetics reasoning often try to do. There is a sudden burst of entropy in the system just before the change takes place, which the researcher (therapist, operations engineer) would want to measure and monitor.

An important connection here is that the phase shift that occurs in self-organising phenomena *is* a cusp catastrophe function (Gilmore 1981). Researchers do not always describe it as such, but the equation they generally use to depict the process is the potential function for the cusp; the only difference is that sometimes the researchers hold the bifurcation variable constant, rather than treating it as a variable that is manipulated or measured in the study.

Figure 7 is a common expression of the phase shift. The little ball, which indicates the state the system is in, is stuck in a low-entropy well that represents an attractor. When sufficient energy or force is applied, the ball comes out of the well, and with just enough of a push it moves into the second well. In some situations we know what well the system is stuck in, but not necessarily the nature of the well it needs to visit next. The question of how to form a new attractor state is a challenge in its own right.

Figure 7. Two-well phase shift.



The essence of emergence is that, ‘The whole is greater than the sum of its parts’. This maxim has been attributed to Aristotle (Gorman 2014), the Gestalt psychologists of perception, and Durkheim (Sawyer 2005). For Durkheim, a scientific study of sociology needed to study phenomena that could not be reduced to the psychology of individuals. The essential solution was as follows: The process starts with individuals who interact, do business and so on. After enough interactions, patterns form and become institutionalised or become institutions. When an institution forms, it has a top-down effect on the individuals such that any new individuals entering the system need to conform to the demands, which are hopefully rational, of the overarching system.

Emergent events can be light or strong. In the light version, the overarching structure forms but does not have a visible top-down effect. In the strong situations, there is a visible top-down effect. Two further types of emergence are frequently observed in live social systems. One is the phase shift dynamic. The second is the avalanche dynamic that produces $1/f^b$ relationships. Physical boundaries also place constraints on emerging phenomena. For instance, the social dynamics of a group of people can be shaped by the location of furniture in a room.

2.6. Synchronisation

The dynamics of synchronisation follow from those of self-organisation and emergence generally and driver–slave relationships more specifically. Whereas a driver–slave relationship is unidirectional, synchronisation phenomena are bi-directional or N-directional. A prototype illustration is synchronisation of a particular species of fireflies, as told by Strogatz (2003): In the early part of the evening the flies flash on and off, which is their means of communicating with each other, which they do at their own rates. As they start to interact, they pulse on and off in synchrony so that the whole forest lights up and turns off as if one were flipping a light switch. The common features among the many other examples are that synchronised systems contain two oscillators, a feedback loop between them, and a control parameter that speeds up the oscillation. When the speed reaches a critical level, *phase lock* sets in and the synchronised pulsing can be observed. Synchronisation has become an interesting component of team coordination dynamics, as discussed in Sections 4.9 and 4.10.

2.7. Agent-based Modelling

If a system contains thousands of agents that interact randomly, it becomes virtually impossible to calculate all their outcomes from those interactions at an individual level. Thus, computer programs known as agent-based models were developed to determine final system states – evolutionarily stable states – given the complexity of all the agents' interactions (Axelrod, 1981; Maynard-Smith, 1992). Agents interact according to specific rules defined within the theory that is being programmed. Agent-based models are closely related to several other computational systems that illustrate self-organisation dynamics. Some of the principles are developed by Axelrod and Maynard-Smith surface in the theory of team coordination (Section 4.9).

2.8. The complex adaptive system

The concept of a *complex adaptive system* (CAS) can describe virtually any living system, although in the present context we are thinking primarily of multiple interacting person–machine systems. The CAS originated in biology (Gell-Mann 1984), and, in some circles, has become the new dominant model of organisational behaviour (Anderson 1999; Allen, Maguire, and McKelvey 2011; Dooley 1997, 2004). The perspective incorporates the NDS concepts that have been described already to study patterns of behaviour as they unfold over time: how the system recognises signals and events in the environment, harnesses its capabilities to make effective responses, changes its internal configurations as new adaptive responses require and interacts with the external environment.

The *schema* is the building blocks of the behaviour patterns, as seen in the development of psychomotor skill (Newell 1991). Schemata also bear a strong resemblance to perception-action sequences as defined in Gibson's (1979) ecological perspective on perception. Schemata also depict rules of interaction with other agents that exist within a system or with agents outside the system's boundaries (Dooley 1997). A team's schemata are often built from existing building blocks that are brought into the group when members arrive. Dominant patterns emerge from interactions among agents, and they often have a top-down influence on incoming agents. Although the individual schemata self-organise into one or more supervening mental models, there can be individual differences remaining that could provide enough entropy for further modification of the schemata.

Schemata change through mutation, recombination and acquisition of new ideas from outside sources. Change occurs in response to both changing environments and changing internal conditions. Indeed, there are numerous sources of entropy that could arise from changes in other agents in the environment, the capabilities of the incoming work force, technologies, products, markets and governmental regulations (Bailey 1994; Bigelow 1982; Guastello 2002). When schemata change, requisite variety, robustness and reliability are ideally enhanced (Dooley 1997). *Reliability* denotes error-free action in the usual sense. *Robustness* denotes the ability of the system to withstand unpredictable shock from the environment. *Requite variety* refers to Ashby's (1956) Law: For the effective control of a system, the complexity of the controller must be at least equal to the complexity of the system that is being controlled. *Complexity* in this context refers the number of system states, which are typically conceptualised as discrete outcomes.

The reliability and robustness of a system are not guaranteed. Schemata and the CAS as a whole undergo evolutionary and sometimes revolutionary change as their schemata self-organise further to enhance fitness and functionality. Increased levels of contradictions within the system's schemata are precursors of higher entropy levels in system performance, which are in turn precursors of an impending phase shift. This principle has been identified as symmetry-breaking (Prigogine and Stengers 1984; Sulis 2009).

A complex *adaptive* system remains poised 'on the edge of chaos' or far-from-equilibrium conditions ready to reorganise itself in response to new demands. The sequence of states through which it reorganises are relatively unpredictable, although at some point it should be possible to envision possible future scenarios and states; again some people are better at system forecasting than others (Heath 2002). A team's particular sequence of stages is often subjected to initial conditions which contribute to the global unpredictability of the system. The states of team organisation are irreversible once they have taken hold and stabilised (Dooley 1997). Although teams can redeploy old schemata, the effect is not the same because of the history that accumulated, events that occurred and time that has elapsed.

3. Nonlinear methods

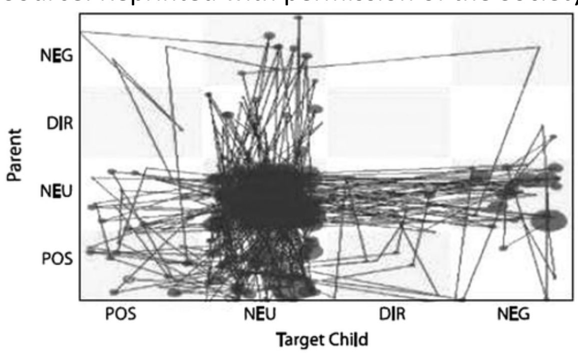
The constructs described here are not simply enchanting metaphors. They are analytic, meaning that it is possible to assess empirically which dynamics are occurring when, how and under what conditions. There are equations representing these phenomena that can be computed with real data assessed statistically.

Nonlinear methods can be organised into three broad categories that are associated with the objectives of mathematicians, biologists and physicists, and social scientists (Guastello 2009a). The social scientists' perspective on data handling falls closest to the concerns for research in ergonomics. Their strategy arises from their history of developing linear models and separating them from 'error'. A nonlinear model, chaotic or otherwise, also needs to be tested statistically and separated from residual variance. That said, we can provide an overview of the analyses that have had the largest impact on nonlinear human science, some of which are fundamentally mathematical, and others derive from extensions of statistical theory. The interested reader should see Guastello and Gregson (2011) for expansions on each technique.

3.1. Phase-space analysis

A phase space diagram is a picture of a dynamical process that can tell us quite a bit about the behaviour of a system that follows a particular function. It is usually drawn as a plot of the change in X (ΔX) at time $t + 1$ as a function of X at time t – velocity versus position. The attractors shown in Figure 4 are phase space diagrams. There are a few other varieties of phase space diagram such as plots of two variables and the *state space grid* (Figure 8; Hollenstein 2007).

Figure 8. State space grid depicting a high-entropy and high conflict relationship, from Dishion et al. (2012, 346). Source: Reprinted with permission of the Society for Chaos Theory in Psychology and Life Sciences.



Phase-space analysis for real data has been problematic, however, because it does not provide any inferential statistics by itself, and the look of the diagram can be seriously affected by noise, and projection in an inadequate number of spatial dimensions. Problems of noise and spatial projection are generally handled through combinations of filters and analysis such as *false nearest neighbors* (Shelhamer 2007). Problems with statistical inference are typically handled a few different ways. One can start with non-statistical calculations such as the correlation dimension, the Lyapunov exponent, or the Hurst exponent on a time series (see the next sections of this article); from there one can compare the results of a single target time series against surrogate samples. If experimental conditions are involved, compare the various metrics found in each condition. Another class of alternatives is to use a statistical analogue of the metric.

3.2. Correlation dimension and surrogate data analysis

The *correlation dimension* is a computation of a fractal dimension for a time series. The 'correlation' in its name reflects that it is looking for long-range patterns of behaviour and measuring their structure (Grassberger and Procaccia 1983). The basis of the procedure is to treat the time series as a complicated line graph and cover it with circles of radius r. Count the number of circles required, then change the radius and repeat many times. Then correlate the log of the number of circles required with the log of the radius. The result will be a line with a negative slope. The absolute value of the slope is the fractal dimension.

Some of the earliest NDS studies that used correlation dimensions attempted to draw a conclusion about the underlying dynamics from a single time series. On the one hand, researchers correctly observed that there was much more information in a time series compared to what was possible with conventional experimental designs. On the other hand, the problem of making generalisations from case studies still persists. The solution was to develop surrogate data by generating many time series by reshuffling the observations in the original time series. This step would preserve means and variances, but would disrupt the serial dependency among the observations. One then compares the correlation dimension (or other metric) from the target time series with those taken from the surrogate samples, and computes a one-sample z or t test to determine if the value from the target series could have occurred by chance.

3.3. Lyapunov exponent and entropy

In light of the large number of known chaotic systems, researchers in applied contexts usually focus on the generic properties of chaos and how it might be differentiated from other nonlinear dynamics. The test for chaos is currently performed with the Lyapunov exponent, which measures the amount of turbulence in a time series. It is calculated from sequential differences in values of the behavioural measurement and the extent to which the differences expand and contract. Larger values indicate faster information loss in a system as one attempts to predict the state of the system into many points into the future. There is also a statistical analogue of the Lyapunov exponent that can be calculated through nonlinear regression.

Chaotic time series contain both expansions and contractions. The Lyapunov exponent was first conceptualised as a spectrum of values calculated by taking a moving window of three observations and compiling them across the entire time series. The largest value in the spectrum is the most critical. If it is positive, the series is expanding and potentially chaotic. Furthermore, there would be many negative values corresponding to the contracting component. If the largest value is negative, however, the series is contracting only, and veering towards a fixed point. If the largest value is 0, then the system is a perfect oscillator. A slightly negative largest exponent indicates a dampening oscillator, which tends towards a fixed point eventually. A slightly positive largest exponent is aperiodic, and could be moving into more interesting regimes such as SOC, Levi flights and chaos.

The positive values of the Lyapunov exponent, λ, are more readily interpreted by converting it to a fractal dimension, $D_L = e^{\lambda t}$; where t = time units elapsed, which are usually set equal to 1.0. D_L is usually called a *Lyapunov dimension* when it is calculated in this manner. The interpretation of dimension values given λ in section 2.2 applies here.

3.4. Hurst exponent

The Hurst exponent, H, was first devised as a means of determining the stability of water levels in the Nile River. Water flows in and flows out, but does the net water level remain relatively stable or does it oscillate? To answer this question, a time-series variable, X with T observations is broken into several subseries of length n; n is arbitrary. Then for each subseries, the grand mean is subtracted from X, and the differences summed. The range, R, is the difference between the maximum and minimum values of the local means. Then rescaled range, $R/\sigma = (\pi n/2)^H$, where σ is the standard deviation of the entire series; $0 < H < 1$. Actual values of H may vary somewhat due to the choice of n and the time scale represented by the individual observations.

A value of $H = 0.5$ represents *Brownian motion*, meaning that the deflections in a time series can be upward or downward with equal probability on each step. Brownian motion has a Gaussian distribution and is non-stationary. Values that diverge from 0.5 in either direction are non-Markovian, meaning that there is memory in the system beyond the first step prior to an observation.

$H > 0.5$ denotes *persistence*. Deflections in a time series gravitate towards a fixed point if they are high enough. The autocorrelation of observations in a time series is positive. Values in the neighbourhood of 0.75 represent pink noise or self-organising systems. $H < 0.5$ denote anti-persistence; upward motions are followed by downward motions, and the autocorrelation is negative.

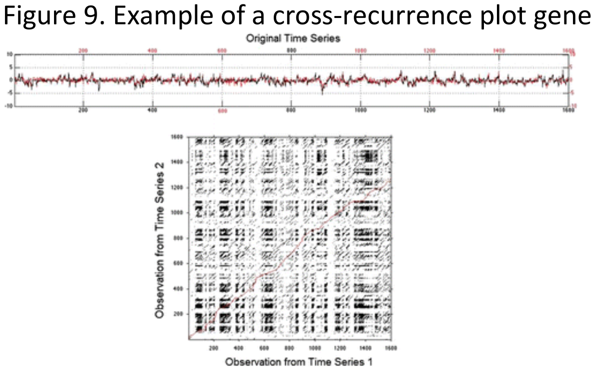
Negative values of H have also been reported (Guastello et al. 2014). When they occur, they are indicative of hysteresis around a bifurcation manifold, such as the one contained in a cusp catastrophe. Oscillations and hysteresis may appear similar, but topologically they are not.

3.5. Recurrence quantification analysis and plots

Although chaotic functions are said to produce non-repeating patterns, repeatability is really a matter of degree. Visualising what repeats and how often can provide new insights into dynamics of a process. A recurrence plot starts with a time series. The user specifies a *radius* of values that are considered to be similar enough and a *time lag* between observations that should be plotted. If the same value of $X(t)$ appears at $X(t + 1)$, a point is plotted. The variable itself appears on the diagonal. One can also examine the *cross-recurrence* between two variables by substituting a $Y(t + 1)$ for $X(t + 1)$.

White noise would produce a plot containing a relatively solid array of dots with no patterning. An oscillator would produce diagonal stripes. More interesting deterministic functions would produce patterns; an example of a cross-recurrence pattern that was generated from two galvanic skin response series appears in Figure 9. One can then calculate metrics that distinguish one pattern from another such as the percentage of total recurrences, percentage of consecutive recurrences and the maximum length of the longest diagonal (shorter is more chaotic). A time series is interpreted as being more deterministic to the extent that more points line up on the central diagonal. The patterning of other points is often described as pink, or $1/f^b$, noise.

Figure 9. Example of a cross-recurrence plot generated from two galvanic skin responses times series.



3.5. Nonlinear statistical theory

There is another genre of analysis that starts with a relatively firm hypothesis that a particular nonlinear function is inherent in the data. The function could be chaotic, reflect other types of dynamics or perhaps be flexible enough to discern the underlying dynamics from the results produced. Consistent with four goals of inferential statistics, the analyses are devised to predict points, identify the nonlinear dynamics in the data, report a measure of effect size and determine statistical significance of the parts of the respective models. Other fundamental issues concern probability density functions, the structure of behavioural measurements and the stationarity of time series.

Students of the behavioural sciences in the late twentieth century were taught to divide their probability distributions into four categories: normal (Gaussian) distributions, those that would be normal when the sample sizes became larger, those that would be normal if transformations were employed and those that were so aberrant that non-parametric statistics were the only cure. In the NDS paradigm, however, one is encouraged to assume specific alternative distributions such as power law, exponential and complex exponential distributions. Differential functions can be rendered as a unique distribution in the exponential family, and the presence of an exponential distributions or a power law distribution in a time series variable denotes a nonlinear function contained therein.

The classic notion of a mental or behavioural measurement, following from Lord and Novick (1968) is that a measurement consists of two components – a true score and an error score. The true score is not really observable because of the presence of error. Errors are thought to be normally distributed with a mean of 0, and are uncorrelated with any other errors, true scores, or anything else. The two elements decompose, however, when the same observed measurement is put into a time series. The true score follows a function of some sort that could be linear but could also be nonlinear. Locally linear functions are often embedded in globally nonlinear functions to different degrees. The error score divides into two components: the classic independent error and dependent error. The independent error component is called IID, or *independently and identically distributed error* when it occurs in a time series.

Dependent error in a dynamical process might occur as follows: Imagine we have a measurement that is iterating through a process such that $X_2 = f(X_1)$. The function produces X_3, X_4, etc. in the same way. Now let a random shock of some sort intrude at X_4. At the moment the shock arrives, the error is IID. At the next iteration, however, $X_5 = f(X_4 + e)$; the error continues to iterate with the true score through the ensuing time series.

Dependent error also occurs when errors are autocorrelated or when complex lag effects are in play such that $X(t) = f[X(t-1), X(t-3)]$. Fortunately, there is a proof showing that the presence of dependent error in the residuals of a linear autocorrelation is a positive indicator of nonlinearity (Brock et al. 1996). Furthermore, it follows that, if a good-enough NDS function is specified for the iterations of the true scores, the dependent error is reduced to a nonsignificant level (Guastello 1995).

Specification of a good-enough nonlinear function requires that the dynamics for the phenomenon have been theorised in sufficient detail. Although there are no automatic procedures for finding the optimal nonlinear model for a problem, there are some good options that have some reasonable flexibility. Consider two examples:

$$\Delta z = \beta_0 + \beta_1 z_1^3 + \beta_2 B z_1^3 + \beta_3 A$$

(3)

$$Z_2 = \theta_1 B z_1 * \exp(\theta_2 z_1) + \theta_3$$

(4)

where z is the dependent variable (order parameter) that is measured at two or more points in time, A and B are control (independent) variables, β_i are linear regression weights and ϑ_i are nonlinear regression weights. For models similar to Equations 3 and 4, data are prepared by setting a zero point and a standard calibration of scale for all variables in the model. Any error associated with approximating a differential function from a difference function becomes part of $[1{-}R^2]$.

Equation 3 is a cusp catastrophe executed with ordinary polynomial regression. There are also alternatives for evaluating catastrophe models by determining the extent to which the data fit a probability density function that is unique to the model. This method might be chosen in cases where the time-1 value of the order parameter z is 0 for all cases, or if the data-set has been collected to measure the behaviour at one point in time only (Guastello 2013; Guastello and Gregson 2011).

Equation 4 is part of a series of exponential models (Guastello 1995; 2011). In Equation 4, ϑ_2 corresponds to a Lyapunov exponent; if ϑ_2 is positive and ϑ_3, the constant, is negative, then both expanding and contracting properties exist in the data-set. That combination of results in turn denotes chaos. One can then convert ϑ_2 into a Lyapunov dimension to interpret the dynamics further.

There is also a series of models for identifying oscillators and coupled oscillators (Boker and Graham 1998) that starts with the assumption that the time series contains an oscillator:

$$d^2X\,(t)\,/\,dt^2 = \beta_1\,(dX\,/\,dt) + \beta_2 X$$

(5)

The left-hand side of Equation 5 contains an acceleration of the time-series variable. The right-hand side contains its velocity and position. The model can be modified by adding components, such as a cubic term denoting a hard or soft spring or influences from another oscillator (Butner and Story 2011).

It should be emphasised that the statistical analyses are intended for *modelling, not curve-fitting*. Of course one wants to see statistical significance and large effect sizes, but the target nonlinear model should be compared against alternative theoretical models. The alternatives are often linear but not always so. The comparisons would involve not only effect size, but also whether the components of the model that represent the critical dynamics are all present.

3.6. Markov chains

Markov chain analysis originated outside the realm of nonlinear science, although it was intended for problems that are very similar to some found in NDS. The central idea is that the researcher is observing objects or people in a finite set of possible states. All objects have odds of moving from one state to another. The State *X* State matrix of odds is known as a *transition matrix*. The goal of the analyses is to establish the transition matrices and to predict the arrival of objects into states.

Some combinations of transitions result in fixed points, oscillators, bifurcations and chaotic outcomes (Gregson 2005, 2013; Merrill 2011). Thus, Markov chain analysis now falls within the scope of nonlinear dynamical analyses for categorical data.

3.7. Symbolic dynamics

Symbolic dynamics is an area of mathematics that finds patterns in a series of qualitative data. The elementary patterns themselves can be treated like qualitative states and analysed for higher order patterns. The class of techniques is ideally suited to analysing chaotic and related complex nonlinear dynamics, either in the form of continuously valued time-series or qualitative categorical data. Symbolic dynamics are particularly useful in situations where discontinuities, continuities, periodic functions and unnamable transients could co-exist within a relatively short time series.

For continuous data, events such as spikes and small or large uptrends and downtrends are coded nominally (eg with letter codes A, B, C, D, etc.) and then analysed. The computational procedures often include entropy metrics. For categorical data, the categories, which should be defined in a theoretically relevant way, are also given letter codes, and the computations are carried out the same way and produce the same metrics.

The algorithms that are available vary in their means for determining symbol sequences and the length of those sequences. The *orbital decomposition* procedure (Guastello, Hyde, and Odak 1998; Guastello, Peressini, and Bond 2011; Peressini and Guastello 2014), for instance, begins with the assumption that the time series *could* be chaotic, but chaos is not specifically required. According to a theorem by Newhouse, Ruelle, and Takens (1978), three coupled oscillators are minimally sufficient to product chaos. The central algorithm disentangles periodic patterns, and it is particularly good for empirically determining the optimal pattern length and isolating dominant patterns. It includes statistical tests for determining the extent to which the set of patterns isolated by the analysis deviate from chance levels of occurrence. Two of its application areas that are of interest to ergonomics are communication patterns in groups or teams (Guastello 2000) and task switching (Guastello et al. 2012).

4. Selected applications

Applications of NDS span *most* of the range of topics that are of current concern in ergonomics: psychophysics, visual displays, controls, neurocognitive processes, psychomotor functioning, stress and fatigue, accident analysis and prevention, and artificial life and complex systems. The state of the science on these matters is still evolving (Guastello 2014a). The selections that follow collectively emphasise a broad range of nonlinear principles.

4.1. Nonlinear psychophysics

Some of the more perplexing problems in psychophysics involve the detection of signals that appear and disappear irregularly as either the signal source moves through space or as the operator moves about. The prototype of the operator sitting in front of a display screen to which all the events are confined is only representative of a portion of real-world events. If the signal has multiple properties that need to be present, the detection challenge increases in complexity as well.

Nonlinear psychophysics (Gregson 1992, 2009) addresses this broad class of problems. Its centrepiece is the gamma function:

$$\Gamma: Y_{j+1} = -a(Y_j - 1)(Y_j - ie)(Y_j + ie)$$

(6)

(Gregson 1992, 20). Equation 6 states that the strength of a response to a stimulus, *Y*, at time *j* + 1 is a function of the response at a previous point in time, *j,* a control parameter representing physical signal strength *a,* a situational control parameter *e,* and the imaginary number $\sqrt{-1}$. Response strength might be measured as a subjective numerical rating, although the preferred method would be to measure response time. The shorter response times will be required for stronger stimuli. It is noteworthy that as the signal strength becomes sufficiently weak, the pattern of responses over time becomes chaotic.

Equation 6 can be expanded to two response parameters that may be useful for modelling cross-modality responses, such as interpreting a hue of a coloured light from the perception of its brightness only, or studying the size–weight illusion. Two-dimensional outcome expansion is accomplished by substituting a real number, *x,* for *i*:

$$X_{j+1} = a\left(e^2 - e^2 X_j + X_j^2 - Y_j^2 - 3X_j Y_j^2 - X_j^3\right)$$

(7)

$$Y_{j+1} = aY_j\left(-e^2 + 2X_j - 3X_j^2 + Y_j^2\right)$$

(8)

(Gregson 1992, 44). Γ is further expandable into multidimensional inputs and outputs that were applied to real situations such as perceiving the taste of wine.

If one were to plot the perceived signal strength *Y* against ranges of *a* and *e*, one obtains not only the familiar ogive, but an escarpment of ogives with varying degrees of steepness (Gregson 2009). If one were to follow changes in *Y* over time as *a* and *e* vary, one can observe hysteresis around the underlying absolute threshold. Hysteresis around the threshold was known since Weber and Fechner; the solution in classical psychophysics was to use the average value of the two stimulus strengths that correspond to the sudden upswings and sudden downswings in response. Signal detection theory eliminated the hysteresis by randomising the stimuli that were presented to the observers. Randomised stimuli are probably not representative of most real-world events; chaotic or other deterministic flows of stimuli would be more likely.

Parameters *a* and *e*, therefore, are not restricted to constant values. They can be a nonlinear time-series variables as well. In those cases, the dynamics of *X* would be globally unstable as the respondent would go through periods of conscious and unconscious awareness of stimulus changes (Gregson 2013). The situation opens new frontiers in psychophysics research that would involve analysing properties of important stimulus sources, such as continuous camera feeds for vigilance tasks, and devising experiments in which humans respond to analogous stimulus flows with similar properties.

4.2. Nonlinear control theory

The effect of control actions in person–machine system interactions can be discrete, linear, exponentially growing or decaying, or oscillating. Control systems make use of feedback loops, velocities and accelerations. Thus, the stage has been set for a long time to make a smooth transition to nonlinear systems of the types considered here (Jagacinski and Flach 2003). For instance, multiple coupled oscillators can be overserved in rhythmic movements. One can further imagine the potential for chaotic conditions as three or more loosely coupled person–machine systems start to work together.

Modern control systems are growing in complexity, as evidenced by the use of multi-modal control systems and mode errors. How complex should a system be? According to Ashby's (1956) Law of Requisite Variety, a controller should be at least as complex as the system it needs to control. Some of the other applications considered next, however, indicate that complexity beyond requisite variety produces inefficiency.

4.3. Cognitive workload and fatigue

Increasing proportions of the work done each day by millions of people involve cognitive labour. Although computerisation can reduce work to some extent, it can generate new sources of fatigue and workload, particularly if people need to keep up with a fast flow of incoming data or task requests, or to keep up with automatic machine controls that seem to have a mind of their own. The negative effects of cognitive workload and fatigue on performance have been difficult to separate historically because they can both occur simultaneously, even though they might have different underlying dynamics. To complicate matters, coping, automaticity, practice and fatigue recovery have positive effects on performance over time simultaneously with increasing load and fatigue. For extensive background on the problems, see Hancock and Desmond (2001), Ackerman (2011), Matthews et al. (2012), and Hancock (2013). Operators can adapt to changing workloads in order to maintain desired performance levels, but after a point the potential for adaptation ends and catastrophic declines in performance occur (Hancock and Warm 1989). Operators can adapt to fatigue and boredom by switching tasks, but task switching incurs additional load on working memory (Guastello et al. 2012). Furthermore, the performance decrement that occurs with fatigue can be relatively gradual or severe, depending on the level of workload involved.

The cusp catastrophe models for cognitive workload and fatigue (Figure 4) and their supporting research programme evolved in response to this nexus of difficulties. The overall objective is to separate the two processes, which have the same temporal dynamic structure but different contributing variables, using an integrated experimental design that tests them both in the same situation. The tasks that have been studied were chosen to capture an array of cognitive processes and to find what was generalisable about the control variables: an episodic memory task (Guastello et al. 2012), a pictorial memory task that required verbal retrieval cues (Guastello et al. 2012), perceptual-motor multitasking (Guastello et al. 2013), a vigilance dual task (Guastello et al. 2014) a financial decision-making task that captured both optimising and risk taking behaviour (Guastello 2016a) and an N-back task (Guastello et al. 2015).

Each of the workload models was paired with a fatigue model. The common feature of the experimental designs was to define starting and ending conditions that did not confound changes in workload with changes in duration of work. Some experimental procedures produced more of a workload effect than a fatigue effect and vice versa.

The model for cognitive workload invokes the concept of Euler buckling (Guastello 1985; Zeeman 1977). A piece of material that is subjected to sufficient amounts of stress in the form of repeated stretching will show a certain amount of deformity, or strain. Rigid materials break, whereas flexible materials rebound. In Figure 4, performance or response time would be the dependent variable, *y.* The amount of vertical weight is the asymmetry (a) parameter. The modulus of elasticity of the material is the bifurcation factor (b), with low elasticity located at the high end of the bifurcation axis. Psychological constructs that could be candidates as elasticity-rigidity variables should reflect adaptability versus rigidity.

Fatigue is defined as the loss of work capacity over time for both cognitive and physical labour (Dodge 1917; Guastello and McGee 1987). Depletion of work capacity is typically observed as a *work curve* that plots performance over time. Performance *usually* drops sharply under fatigue, but not everyone experiences a decline as result of the same expenditures, however. Some show an increase in physical strength akin to 'just getting warmed up', while others show consistently higher or lower performance levels for the duration of the work period. Fatigue is also accompanied by a higher degree of variability in performance. The cusp response surface (Figure 4) accounts for the full range of possible work curves. Work capacity displays the two stable states. Change in capacity is implied by change in performance. Psychological disengagement, or a drop in motivation, also contributes to performance decrements, although the drop in motivation is also symptomatic of physical or mental fatigue (Balagué et al. 2012; Guastello et al. 2012; Hockey 1997, 2011). At some point, the individual wants to stop working or switch to a different task.

The total quantity of work done between two measurement points would be the primary contributor to the bifurcation parameter: If the individual did not accomplish much in the time allotted, there would be little drain on work capacity. Those who accomplished more work could exhibit either positive or negative changes in work capacity.

The asymmetry parameter would be a compensatory strength measure. In the prototype example, labourers displayed changes in arm strength as a result of about two hours' worth of standard mill labour tasks, which primarily demanded arm strength. Leg strength, however, acted as a compensation factor for arm strength; those with greater leg strength experienced less fatigue in their arms (Guastello and McGee 1987). A similar effect is thought to occur in cognitive work.

The earliest efforts to identify compensatory abilities for the cognitive fatigue model stuck close to the physical labour prototype where the fatigue measure was a drop in capacity and the compensatory ability was a related capacity. Later efforts examined performance differences as the index of fatigue, and the abilities were not always so indirect, eg speeded arithmetic ability relative to the financial decisions task. Meanwhile, theoretically driven research was showing that working memory is part of fluid intelligence (Kane, Hambrick, and Conway 2005; Nusbaum and Silvia 2011). Thus, measures from the fluid domain such as anagrams and algebra flexibility were brought into the mix for testing. Field independence and algebra flexibility now seem to do double-duty as flexibility measures relative to workload and a compensatory ability relative to fatigue.

4.4. Elasticity and rigidity

The cognitive constructs that are part of the bifurcation variable for the workload model have been isolated as a separate subsection here because there is good reason to think that that they could be operable in other situations where the efficacy of a complex adaptive system would be involved. Variables that qualify as elasticity-rigidity constructs have some supporting rationale as bifurcation variables. One pole is associated with positive and negative discontinuities, whereas the other pole may be associated with gradual change or no change in performance at all. Some have contributed directly to the cusp models tested thus far, whereas others were only part of linear comparison models or indirectly related to workload through subjective ratings (Guastello et al. 2015). Five groups of constructs evolved as the project progressed:

(1)	*Trait anxiety* can interfere with lucid decision-making, but it can also focus attention on details that others might miss. At present, anxiety only seems to be operative in contexts with interpersonal challenges or physical hazards. *Emotional intelligence* (EI) facilitates understanding of one's own emotions and the emotional messages from other people and forming appropriate actions in response. Low EI denotes rigidity in the form of indifference, which could be a buffer against stress effects. When stress gets too high, however, the system buckles and snaps in the form of poor decisions (Thompson 2010). *Frustration* can have a negative impact on performance making tough situations worse, but it can also spur the individual onward to work harder or differently.
(2)	*Conscientiousness* is a trait that predisposes one to attention to details, rules and task orientation, and thus implies a type of rigidity. Flexibility or adaptiveness is not expected. *Work ethic* is thought to function in approximately the same way. *Impulsivity* is a facet of conscientiousness and reflects a tendency towards elasticity.
(3)	One construct of *coping flexibility* is centred on emotional adjustments in the sense of long-term life issues (Kato 2012). More flexible people have a broader repertoire of coping strategies they can use. Another type of coping is oriented towards cognitive strategies such as planning, monitoring, decisiveness and inflexible responses to changing work situations (Cantwell and Moore 1996). So far the latter was found more closely related to cognitive workload dynamics.
(4)	*Field independence* is a cognitive style that separates perceptions of a figure from a background. It was also proposed the field independent people use more of their working memory capacity (Pascual-Leone 1970). As such it worked well as a bifurcation variable in studies of problem-solving in chemistry (Stamovlasis and Tsaparlis 2012) and financial decision-making (Guastello 2016a).
(5)	Other degrees of elasticity are inherent in the task structure such as whether operators can choose how to *sequence subtasks*.

4.5. Biomechanics of material handling

The buckling model for workload also provides a viable explanation for back injuries resulting from heavy lifting (Karwowski, Ostaszewski, and Zurada 1992). The load parameter is calibrated as kg/cm^2 of downward pressure on the spine as one lifts a heavy object from the floor or an elevated platform. Pressure is maximum at the moment when the individual stands upright with the object.

Elasticity is inherent in the material comprising the spinal column. Its capacity range can vary as a result of regular exercise, prior injury, brittleness of bones or the person's height relative to the lifting platform. Note the paradox here: Having the arm strength to lift a heavy object can be detrimental if the spine is too rigid to support the peak load. The flexibility in the spine as it moves during a lift has been determined to be chaotic (Khalaf, Karwowski, and Sapkota 2015).

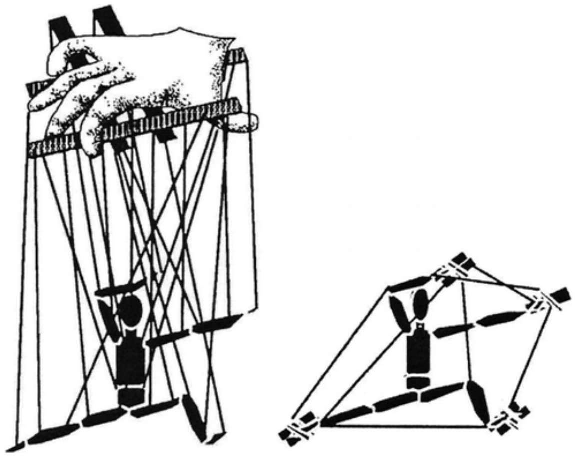
A related problem is the stability of one's balance while carrying the load, particularly while walking across a narrow beam, rather than an ordinary floor. This is common but hazardous occurrence in the construction industry that could lead to falls from heights up to 5 m when individuals lose their balance. Gielo-Perczak, Karwowski, and Rodrick (2009) thus evaluated the natural variability in the centre of pressure that registers on a person's foot while carrying loads, using the Lyapunov exponent. They found greater volatility (deterministic chaos) in the centre of pressure when beams were narrower and loads were heavier. The increased variability is reflective of an adaptive response, but also a tendency towards instability when it becomes too great. The authors also remarked that a steady centre of pressure requires attentional resources that can be compromised by multitasking.

Surface electromyographs (EMG) can detect signs of muscle fatigue. As seen in other context, variability of the wave amplitudes is part of fatigue in addition to the decline in the capacity to perform. Rodrick and Karwowski (2006) hypothesised that the variability is an outgrowth of a deterministic nonlinear process. They compared Lyapunov exponents and fractal dimensions for EMG taken from participants in a lifting task and found that there were significant differences in both nonlinear metrics depending on the lifting posture. The task itself involved only differences in lifting posture and not external load. Future research could expand on these findings to establish load–fatigue relationships.

4.6. Degrees of freedom in movement and cognition

The principle of degrees of freedom underlies several types of self-organising dynamics. The idea was first introduced to explain the control of physical movement (Bernstein 1967; Turvey 1990). If all the movements of the marionette in Figure 10 were under control of an executive controller, it would take as many degrees of freedom to effect a movement as there are stings shown in the left diagram. If the system were self-organised, however, a much smaller number of degrees of freedom would be needed to create the same movement.

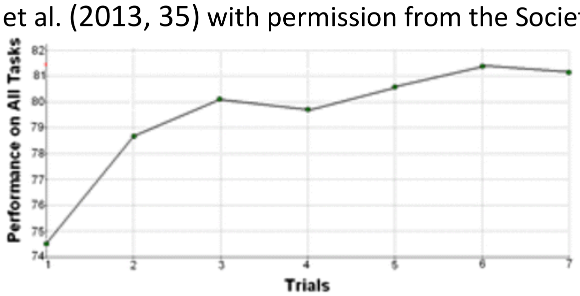
Figure 10. Degrees of freedom in the control of movement under complete executive control (left) and as a self-organised system (right). Source: Reprinted from Turvey (1990) with permission of the American Psychological Association.



The same idea appears to operate in some cognitive processes. When a task is first learned, several possible ways of performing are explored; some degrees are perceptual-motor, others are cognitive. Still others are inherent in the task itself, which might permit re-ordering or combining steps. Eventually, a path of least effort is discovered and adopted for continued use; this is *minimum entropy principle* (Hong 2010). The system self-organises with practice; the involvement in the executive function of working memory can be reduced, and task execution becomes more automatic (Lorist and Faber 2011). Efficiency conceived in this fashion reduces the variability of performance, but some variability needs to remain to facilitate further adaptations. Adaptation to work load could involve a reduction in executive control, which might not be beneficial.

The increase in performance variability and the performance decline signal two possible events. Either a strict minimum entropy effect ensues whereby the individual stops work, or a *redistribution* of degrees of freedom (Hong 2010) occurs so that the individual does something differently, uses different degrees of freedom configurations and gets a ‘second wind’. Figure 11 depicts the performance of 105 people performing seven different tasks seven times each in four possible orders. All bends in the curve were statistically significant according to the trend analysis. Here we see the beginning of a performance drop at trial 4, a recovery and new peak at trial 6 and a second decline.

Figure 11. Performance on seven trials of seven tasks in four possible orders. Source: Reprinted from Guastello et al. (2013, 35) with permission from the Society for Chaos Theory in Psychology and Life Sciences.



4.7. The performance-variability paradox

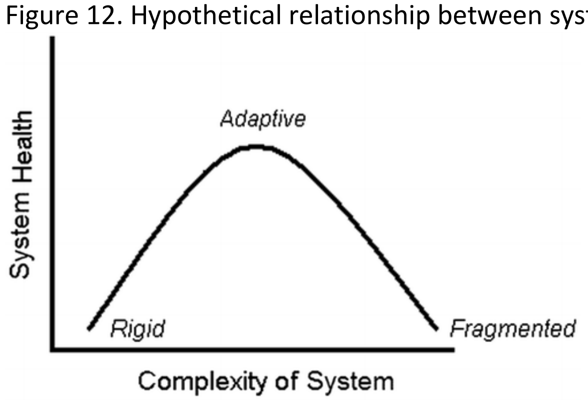
The minimum entropy principle holds that, as one learns to do a task, the learner finds ways of making physical and mental motions as efficient as possible with a minimum of wasted motion or decision time. Guastello et al. (2013) considered two conflicting influences on performance as it unfolds over time. First, 'Best' performers are also expected to be consistent performers, but some variability is needed to remain adaptable to chance events as they arise. Ashby's law of requisite variety is promoting the maintenance of high levels of internal complexity in order to response effectively to the demands of incoming stimuli. Variability is also necessary if performance capabilities are ever going to improve further. Second, *voluntarily* switching tasks can reduce fatigue, but it incurs a workload cost because of the added quantity of information we need to keep active in our working memories. System-driven switching, however, is likely to increase fatigue, (Hancock 2007).

When left to their own discretion, the participants in a study that involved seven perceptual-motor tasks gravitated towards four different task-switching strategies (Guastello et al. 2012): (a) *task first,* in which they completed all of one type before moving on to another; (b) *Set-first*, in which they completed set of (sub)tasks then repeated the sequence; (c) a *mixed strategy* that appeared to include patterns from task-first and set-first strategies; and (d) a *random strategy*. Given the way the study was designed, task-first produced the smallest number of task switches, and a relatively low level of entropy with respect to patterns of task choices. Set-first produced the smallest level of entropy, but the largest number of switches. The analysis of performance results reflected a trade-off between the switches and entropy; the best performers minimised both to the extent possible. On the one hand, only about 50% of the participants engaged in one of the two efficient strategies. On the other hand, the exploration of the tasks was probably a motivating factor for some of the participants. The pattern extraction was performed by the orbital decomposition method. Abilities and elasticity-rigidity variables added to the prediction of performance in the multitasking experiment.

4.8. Optimum variability

The principles that produced the performance-variability paradox – Ashby's Law and minimum entropy – produce a closely related phenomenon, that of optimum variability. The difference is a shift in emphasis to an inverted-U relationship between the level of system complexity and the health or functionality of the system (Figure 12).

Figure 12. Hypothetical relationship between system variability or complexity and system health.



The principle of optimum variability originated with Goldberger (1991, 1997) and Cecen and Erkal (2009) who discovered that healthy heartbeats are chaotic over time, not rigidly periodic. Rather, a cardiac infarction is imminent if the electrocardiogram reveals strict periodicity. The principle generalises to a range of medical pathology problems (Bianciardi 2015; Vargas et al. 2015), psychomotor performance in sports and rehabilitation (Harrison and Stergiou 2015; Kiefer and

Myer 2015; Morrison and Newell 2015) and cognition and work performance more generally (Corrêa et al. 2015; Navarro and Rueff-Lopes 2015). The condition of too much complexity has not been isolated in every instance. When it has been found, however, it is indicative of a poorly controlled system, such as psychomotor function after a patient has experienced a stroke. There are several ongoing research efforts to develop robotic tools that can force neuroplasticity towards and through neural pathways that remain undamaged (Guastello, Nathan, and Johnson, 2009).

The measurement of variability in the optimum variability studies varies by type of data and the options available at the time the research was conducted. Fractal dimensions and entropy metrics are often used (Schuldberg 2015). Although it could be tempting to compare standard deviations, the standard deviation does not capture any of the temporal dynamics in sequential observations, nor can it render a measurement of complexity that is scale-free, such as the fractal dimension. Scale-free metrics are independent of the actual standard deviation of the sample (Guastello and Gregson 2011).

4.8. Occupational accidents

Given the impact of stress on cognitive functioning, it is not unreasonable to surmise that stress has a substantial impact on industrial accident rates as well. If we all lived in rubber rooms, the consequences of stress would be limited. Ironically, the extant literatures on stress and environmental hazards have only considered one or the other influence on accidents (except perhaps on rare occasions). The two sources of influence were assembled into a cusp catastrophe model for the accident process in Guastello (1988, 1989), such that hazards contributed to the asymmetry parameter, and a variety of psychosocial variables, collectively labelled *operator load*, contributed to the bifurcation parameter. The cusp model for occupational accidents has been illustrated and compared for manufacturing, public transportation and health care settings (Guastello 2003).

Safety climate, which was first introduced by Zohar (1980), was part of the *operator load* parameter and tended towards lowering risk levels for an individual or group. Operator load (Guastello 1989) also included stress indicators, anxiety, beliefs about accident control, work-group size and work pace. Reason (1997) noted that work pace by itself can have what amounts to a hysteresis effect on accident rates: An organisation might make a concerted effort to reduce accidents, including adjusting work pace. Eventually, however, the organisation starts to demand higher production output, and, as a result, the organisation starts to zigzag up and down until the control point lands on the 'up' level of the cusp response surface.

The most recent study with the accident cusp (Guastello and Lynn 2014) responded to a meta-analysis (Clarke 2006) showing that safety climate had a generalisable relationship to safety behaviours but not to actual accident incidences or rates. Several things were thought to be missing from the simplistic correlation data: the cusp structure with hazards as the asymmetry parameter, the characterisation of safety climate as a bifurcation variable and anxiety as another bifurcation variable. Anxiety could have either a positive or negative impact on safe outcomes. It would interfere with response time to emergency situations and interfere with clear decisions, or it could be symptomatic of hypervigilance for unsafe conditions.

The participants were 1,262 production employees of two steel-manufacturing facilities who completed a diagnostic survey that measured safety management (akin to safety climate), anxiety, and two types of hazard that were salient in that industry. The accident variable was also collected by a survey item in which the individual gave the number of OSHA-reportable accidents they had in the preceding three years. Because the survey was given at only one point in time, the static cusp model was used for the analysis.

Nonlinear regression analyses showed, for this industry, that the accident process could be explained by safety management, anxiety, hazards, and age and experience within the cusp structure (R^2 = .72). All parts of the cusp model were sustained. The alternative multiple linear regression with anxiety, safety management, hazards and age and experience was substantially less accurate (R^2 = .08). The results thus illustrated the advantages of framing accident problems through the nonlinear paradigm.

4.9. Resilience engineering

The concept of resilience in ergonomics (Hollnagel, Woods, and Leveson 2006; Sheridan 2008; Woods and Wreathall 2008) presents questions such as: How well can a system rebound from a threat or assault? Can it detect critical situations before they fully arrive? Building resilience into a system requires more than the analysis of accidents in hindsight or implementing a right-minded plan. It involves regular monitoring of the system for its proximity to critical situation, anticipating possible critical situations and taking action to adapt as necessary.

In this line of thinking, strain is an independent measure. In the low to moderate regions of strain, the outcome is a fairly consistent increase in the system's ability to meet demands of various types. Beyond a certain point, however, more strain is producing diminishing increments of capability in what the theorists call the 'extra region'. At the extreme of the extra region, the system faults. One would then look for a good place in the process to introduce an adaptation that would stretch the capability of the system.

The definition of a pre-emptive strategy requires a good sense of how a CAS operates. A CAS uses sensors that take the form of information gathering capabilities that can inform organisational members of changing events in the outside environment or internal operations. The most useful information inflows result in the system-level equivalent of situation awareness. Woods and Wreathall (2008) characterised this form of situation awareness as *calibration*, which is to know where the system is located along the stress-demand function in spite of changing circumstances.

A second feature of the CAS, which is not independent of the first, is to have a clear sense of how the system is organised for work and information flows. Here one should look for *functional resonance*, which is how the variability associated with one part of the process crosses to the adjacent parts of the process and travels through the system (Hollnagel 2012; Leonhardt et al. 2009). It would be then be possible to pinpoint non-resilient or non-adaptive features of the process. Non-resilient or non-adaptive features of the process often involve automated functions which, traditionally, permit little variation in the process and output and thus work very efficiently for a limited range of circumstances. One is thus looking for degrees of freedom within the system. A resilience event would occur when the human intervenes to make an adaptation that either extends or overrides an automatic process after detecting that a supercritical event was on the verge of occurring.

This construct of resilience corresponds to the rigidity-elasticity principle in the cusp model of mental workload (Figure 4), but it is now examined at level of a broader sociotechnical system. Rigidity, once again, has the benefit of controlling system variability up to a point, after which a decisive fault can be expected. Elasticity and resilience span the region of the surface that contains the cusp point, which is the most unstable point on the surface. It follows that too much flexibility, or resilience capability, can make a system unstable in the long run. Here one should look for features of the system that use too many degrees of freedom (or control) to do a job when fewer degrees of freedom would produce an equivalent result. There is an optimal level of variability associated with high levels of performance (Leonhardt et al. 2009), which is needed to generate an adaptive response.

4.9. Team coordination

Coordination occurs when two or more people take the same action or compatible actions at the same time or in the correct sequence. Whereas conventional thinking holds that successful coordination requires good communication and a shared mental model, the NDS perspective holds that coordination is fundamentally a nonverbal process, similar to biomechanical coordination, and that shared mental models can self-organise extemporaneously as situations unfold (Guastello 2009b; Guastello and Guastello 1998). The latter point was reflected in an example from Hurricane Katrina (Morris, Morris, and Jones 2007, 99) and in the concept of dynamic situation awareness (Chiappe, Strybel, and Vu 2015). Verbal communication does expedite the coordination process, nonetheless.

Different tasks can require different types of coordination, which are distinguished by the utilities for the group that are associated with different individual actions. Several types of coordination were defined in game theory. Although game theory pre-dated NDS as we know it today, its notions of equilibria that are associated with dominant strategies reflect attractors on some occasions and saddles on others. The connection with NDS consolidated more strongly with the works of Axelrod (1984) and Maynard-Smith (1982) who studied the long-run outcomes of repeated games, which are now known as *evolutionarily stable states*.

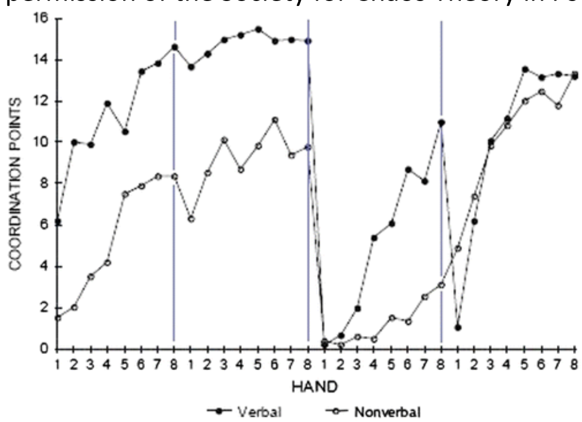
Axelrod and Maynard-Smith studied the Prisoners’ Dilemma game, which required players to make a choice between a competitive and a cooperative option. The more recent game-theoretical studies investigated games that are strictly cooperative, particularly Intersection and Stag Hunt. An Intersection game is modelled after the four-way stop intersection. After approaching a four-way stop intersection with other cars coming from different directions, the goal is to figure out what rules of turn taking are in play for proceeding through the intersection, figuring out when one’s turn comes up, and proceeding through the intersection at the correct moment. Experimental results show that Intersection coordination can occur when the participants are not allowed to talk to each other (Guastello and Bond 2007; Guastello and Guastello 1998; Guastello et al. 2005), including conditions where they only interact through making binary choices on a computer interface (Aruka 2011). Verbalisation does enhance performance, but it is not always necessary for effective performance (Guastello and Bond 2004; Guastello et al. 2005). This is fortunate because coordination among agents must be sustained during communication outages, which are going to occur in emergencies.

Coordination usually occurs as an implicit learning process. *Implicit learning* encompasses the procedures one learns while trying to learning something else explicitly; implicit learning often occurs unconsciously and transfers to new learning situations in much the same way as knowledge gained through explicit learning transfers to new situations (Seger 1994). The Intersection experiments illustrated implicit learning as a transfer of learning that occurred when the participants changed tasks;

the players learned to coordinate, which is separate from learning the task itself. As with other forms of learning, coordinated performance is chaotic in its early stages and self-organised later on (Guastello and Guastello 1998; Guastello et al. 2005).

Figure 13 depicts the performance curves for groups engaged in a coordination-intensive task, 13 of which interacted nonverbally only and 13 were allowed to talk. The task was structured as a card game, which was played in four rounds. The time series for the first round reflected a jagged learning curve. In the second round, the rule changed to a different rule of equal difficulty; the learning curve looked like a continuation of the first one. In the third round, the rule changed to one of greater difficulty. The fourth round reverted to the first rule. The data showed that coordination is learned and that it transfers from one version of the task to another.

Figure 13. Learning curves for team coordination from Guastello and Bond 2007, 104). Source: Reprinted with permission of the Society for Chaos Theory in Psychology and Life Sciences.



Coordination within a group can withstand changes in personnel up to a point, but disruptions in coordination occur when too many group members change; the disruptions are not readily compensated by the availability of verbal channels (Guastello et al. 2005). Group performance can even be enhanced by exchanging personnel with members of other groups who were already trained and coordinated with different people on the same type of task (Gorman et al. 2006). Coordination occurs without any appointed leaders, but leaders do emerge from coordination-intensive situations (Guastello and Bond 2007) *even when the participants are not allowed to talk during the task activity*.

An unconfirmed hypothesis at this stage, however, is that verbalisation during coordination learning becomes increasingly valuable as the task becomes more complex. Verbalisation would include work structuring, role separation and agreements about optimal timing. Coordination learning would be *explicit* in such a context. These elements form the mental model, with the understanding that the model can modify or contain contingencies that can be enacted when the situation changes. The intuitive, implicit, or nonverbal components would still be present, and probably more salient as well. Consider how the best efforts of participants to plan and coordinate are limited by people in the group who are ‘slow to catch on’ or ‘just don’t get it’.

In a *Stag Hunt game*, the players hypothetically choose between working with the group (hunting stag) and working on their own (hunting rabbits). The likelihood of a hunter joining the group depends on the group’s efficacy. The performance of the group depends on the combined skill and efforts of all the hunters. The group outcome can tolerate some individual differences in contributions, but if one member makes too little effort, or too many mistakes, the outcome for the group is reduced to that of the least effective person (Crawford 1991; McCain 1992).

Guastello and Bond (2004) compared the economic game of Stag Hunt, a real stag hunt, an analogous game against a natural disaster, and an analogous game against a disaster that involved a sentient attacker. The key distinction is the dynamics of learning by both the humans and the prey or antagonist. The possible strategic options could be numerous, and the utilities associated with them vary each time the group faces a decision. It is seldom possible, therefore, to predict the evolutionarily stable states of an iterated Stag Hunt without a real-time experiment or simulation (Samuelson 1997). Iterated games of this type are essentially dynamic decisions, as Brehmer (2005) defined them.

Guastello and Bond (2004) operationalised Stag Hunt as a board game (‘The Creature that Ate Sheboygan’) in which an emergency response (ER) team played against a sentient attacker that was trying to destroy a city. The performance of the ER teams and the attackers were recorded over time. The principal findings were that (a) communication outages did not hinder the ER teams’ performance, but attackers did better under those conditions; (b) the attackers improved their performance during consecutive games, which presented an added challenge to the ER teams, whereas ER teams showed both improvements and drops in performance in consecutive games; and (c) the number of ER team members who participated in a particular decision depended on the number of points scored by the attacker on the previous turn; ER team members tended to disengage when the going got tough.

In a later effort (Guastello 2010), the performance dynamics generated by ER teams of 4, 6, 9 or 12 players were analysed for Lyapunov exponents, which were interpreted as an index of adaptability. The comparison of groups sizes would determine whether the performance outcomes favoured smaller groups, which would meant that coordination was impaired, larger groups, which would mean that the larger groups contributed a critical mass of ideas needed for creative problem-solving, or no group effect, which would indicate that no group dynamic self-organised.

The Lyapunov exponent was useful for quantifying entropy and adaptation levels in the performance time series. ER teams operated in the middle self-organising range, suggesting that although they adapted, they stuck with the plans that appeared to have evolved. Attackers, in contrast, exhibited chaotic behaviour: a consistent path of destruction punctuated by opportunistic bursts into different regimes or directions (Lévy flights). Attackers can benefit from such tactics, but ER team members would probably benefit by being more predictable to each other. It is an open question as to whether the teams were as adaptive as they could reasonably be, or what new strategies they would need to deploy to improve.

4.10. Synchronisation

The interest in coordination dynamics has now morphed into an interest in synchronisation. Synchronisation in the behavioural sciences has acquired a few different but related meanings, some of which are not especially different from coordination as it has been discussed to this point. For present purposes, however, the construct of synchronisation that was introduced in Section 2.6 is the prototype construct. One manifestation of synchronisation is specific to psychomotor coordination. In the finger-tapping studies (Haken, Kelso, and Bunz 1985; Kelso 1995; Sleimen-Malkoun et al. 2010), the experimental participants tapped their fingers to a metronome that clicked at a fixed or controlled rate of speed in an alternating pattern of left-right-left-right. When the metronome speed reached a critical point, the two fingers tapped simultaneously rather than alternating. The change from tapping out-of-phase to strictly in-phase is a *phase shift*, and the completely in-phase state is a *phase lock*.

Physiological synchronisation of EEGs, autonomic arousal and behavioural movements between people is thought to be an important component of work team coordination (De Vico Fallani et al. 2010; Delaherche et al. 2012; Guastello, Reiter, and Malon 2015; Henning, Boucsein, and Gil 2001; Salas et al. 2015; Stevens, Galloway, and Lamb 2014; Stevens et al. 2012, 2013) and other interpersonal dynamics. So far, it appears that the degree of coupling between two people is dependent on the task they are performing together, and probably other factors that are still under investigation. These ambiguities affect the lag lengths of the time series of physiological data streams, which in turn affect the rest of the statistical modelling procedure. In the case of a more-or-less ordinary conversation, the coupling was moderated by the empathy levels of the two parties (Guastello, Pincus, and Gunderson 2006; Marci et al. 2007).

The synchronisation links in the sample of dyads have been identified more often and with greater accuracy by Equation 9, compared to a linear alternative:

$$Z_2 \;=\; A\exp(Bz_1) + \exp(CP_1)$$

(9)

In Equation 9, *z* is the normalised behaviour (autonomic arousal) of the target person at two successive points in time, *P* is the normalised behaviour of the partner at time-1, and *A*, *B* and *C* are nonlinear regression weights (Guastello, Pincus, and Gunderson 2006). Equation 5 can also be expanded to incorporate the influence of a coupled oscillator.

Nonlinear time-series modelling requires a strategy for determining appropriate lag lengths. If a measurement at time-2 is a function of itself at time-1 and a coupling effect from another source, how much real time is required to elapse between the two measurements in order to observe the coupling effect? Guastello, Reiter, and Malon (2015) examined four strategies for doing so. In the experiment, 73 undergraduates worked in pairs to perform a vigilance dual task for 90 min while galvanic skin responses (GSR) were recorded. Event rates on the vigilance task either increased or decreased without warning during the work period. Results based on minimum mutual information and a natural rate criterion supported a value of 20 s, whereas two other strategies were not calculable.

The next phase of the project that was based on the same experiment (Guastello 2016b) examined the properties of the linear autoregressive model, linear autoregressive model with a synchronisation component, the nonlinear autoregressive model (first addend of Equation 9) and the nonlinear autoregressive model with a synchronisation component (Equation 9). All models were more accurate at a lag of 20 s compared to 50 s (95 percentile) or customised lag lengths. Although the linear models were more accurate overall by a margin of 4–13% of variance accounted for, the nonlinear synchronisation parameters were more often related to psychological variables and performance. In particular, greater synchronisation was observed with the nonlinear model when the target event rate increased, compared to when it decreased, which was expected from the general theory of synchronisation. Nonlinear models were also more effective for uncovering inhibitory or dampening relationships between the co-workers as well as mutually excitatory relationships. Many aspects of the statistical structures of nonlinear time series that involve synchronisation still need to be investigated.

The adaptive value of high levels of physiological synchrony may require some qualification, however. Stevens, Galloway, and Lamb (2014) discovered that submarine navigation teams whose EEGs were less synchronised were more apt to make adaptive responses to their task when needed; this relationship flipped from negative to positive depending on whether the team was in a briefing, action, or debriefing segment of the simulation. Phase locks in human interaction are probably rare, although they could take the form of rigid conversation patterns in dysfunctional families (Gottman and Levinson 1986; Pincus 2001), which is quite the opposite of a highly functional work team. If synchronisation at the nonverbal level can produce desirable decisions at a more explicit level, it can also facilitate irrationality, particularly if stress and crowding are involved (Adamatzky 2005).

5. Concluding remarks

NDS qualifies as a paradigm of science by virtue of its novel constructs, methods for investigating them, new questions that it poses and the explanations of phenomena it can provide. It qualifies as a general systems theory, and a new paradigm in systems thinking, for the same reasons in addition to the applicability of its principles and methods to nonliving and living systems. The latter range from biophysics to macroeconomics, although the psychological content was perhaps most proximal to ergonomics thus far. Ergonomics, however, has been expanding into micro- and macro-systems, and constructs that provide some continuity among those levels of systems are needed (Karwowski 2012). The scaling principle that is inherent in fractal structures and $1/f^b$ relationships are particularly relevant to this concern.

Systems have also been growing in complexity in the sense of multiple interacting components and multiple outcomes from those interactions. Here, the NDS constructs of chaos and sensitivity to initial conditions, entropy and emergence are well suited for describing and possibly predicting how a system could function (Walker et al. 2010). The principle of degrees of freedom was also introduced here for much the same reason. Add humans to the system, and the former notion of a system is upgraded to the CAS (Dooley 1997; Karwowski 2012). The next question, however, was whether NDS has actually taken root as a paradigm in ergonomics. To answer this question, several streams of research were specifically considered.

Nonlinear psychophysics by itself represents a paradigm shift of a proportion similar to the contribution of signal detection theory relative to classical psychophysics. It is now possible to interpret the double threshold associated with increasing and decreasing signal strengths as the result of a deterministic process. Rather than framing sensation phenomena as stochastic processes in a deterministic environment, nonlinear psychophysics frames the phenomenon as a deterministic process occurring in a stochastic environment (Gregson 2009, 115). Nonlinear psychophysics also accommodates multidimensional stimuli that change over time, and the response variable can be chaotic under some conditions.

Control theory has already built on constructs shared with NDS theory. It is only a matter to take the ideas a few step further to investigate the outcomes from a complex array of controllers working semiautonomously. The new construct, relative to control theory, is Ashby's Law, which is now seen to work in counterpoint with other NDS constructs such as minimum entropy and degrees of freedom.

The NDS perspective on cognitive workload and fatigue has managed to untangle some perplexing questions that have haunted theorists for a century, and accounts for changes in performance under a variety of conditions. The central contribution was the use of two models, not just one, that separate what are often confounding processes. The dynamics of attractors, bifurcations and control variables are part of the catastrophe models. The studies currently on record show that, overall, about one-third of the variance in the performance can be attributed to the nonlinear structure itself (Guastello 2014b). Then, having separated the roles of asymmetry and bifurcation variables it was possible to embark on a productive search for variables that behaved in specific ways. The amount of work accomplished in a given amount of time, which is predicated on workload, feeds into the fatigue process as a bifurcation variable.

The elasticity-rigidity variables that were identified in the workload and fatigue research connect to another important group of questions regarding the resilience of systems. The elasticity-rigidity constructs need to be explored further at a team or larger level of a system. Similarly, the notion of degrees of freedom in fatigue could also explain spontaneous recovery from fatigue and self-organising cognitive processes more generally.

The construct of elasticity versus rigidity originated in material science, as did the first cusp catastrophe model for buckling phenomena. If one considers human and animal bodies as complex and composite materials, the basic cusp model for buckling stress is broadly applicable (Guastello 1985; Karwowski, Ostaszewski, and Zurada 1992). No one, since the beginning of experimental psychology in 1879 has determined what materials constitute the substance of mental structures. If anything, psychologists gave up trying to figure it out decades ago, and many would probably prefer that 'materials' be used in quotation marks. Nonetheless, elasticity and rigidity can be observed in psychological and complex systems; this observation again supports the general systems nature of NDS.

The type of fatigue that was studied in the experiments reported here examined performance fluctuations that occurred in laboratory experiments of about two hours duration and did not extend to the type of fatigue that is produced by sleep deprivation or disruptions of circadian cycles. A useful direction for future research would be to expand the workload and fatigue research to include the circadian influence as part of a more complex dynamical process.

The dual-task methodologies that were used in the early experiments on cognitive workload capacity were fashioned to absorb unused channel capacity with one task while evaluating performance on a target task (Kantowitz 1985). Contemporary work life has induced a small change in perspective such that both tasks are now important, and *multitasking* is a new verb in the workplace. The workload and fatigue studies encountered multitasking as another source of fatigue, and prompted studies on task switching which have some interesting temporal dynamics of their own. Symbolic dynamics and entropy functions were the primary nonlinear methods and constructs. The results converged with other streams of research to produce the performance-variability paradox, which results from the Law of Requisite Variety and minimum entropy principles.

An accident at face value is a discontinuous change of events. As such it looks amenable to analysis with the cusp catastrophe, and in fact it is. When this accident paradigm was first introduced (Guastello 1988, 1989), the objective was to go beyond the traditional single cause, chain-of-events, and other relatively simple models of the process to a model that represents the dynamics comprehensively, including the underlying nonlinearities. The nonlinear properties also describe a process by which situations move from sub-critical to super-critical. The original safety climate (Zohar 1980) remains firm in the single cause mentality. The NDS view is that a safety climate is comprised not only of managerial behaviours and safe actions of operators, but also other environmental influences such as hazards, hazard perception, stress and anxiety levels. The foregoing elements self-organise into social climate that can explain group accident levels and also have a top-down influence on the experiences of individual operators (Guastello and Lynn 2014). The empirical value of this paradigm shift amounts to a much greater explanation of variance in accident outcomes in addition to an explicative model.

The objective of the resilience engineering is to prevent accidental injuries, deaths and other total system failures from happening by rethinking what it takes to make the system a complex adaptive system. Notions of elasticity and rigidity are also involved, although illustrative empirical analyses have not arrived yet. Nonetheless, the idea of system-wide resilience is consistent with NDS theory, and certainly did not originate anywhere else. Surprising events can occur when systems self-organise and situations emerge (McDaniel and Driebe 2005). If a system is sticking too automatically to its operating procedures that have worked well in the past, it can become blind-sided to critical novelties that require an adaptive response.

The NDS studies on group coordination introduced some radical thinking relative to the status quo of the research area: coordination is an implicitly learned response with chaotic and self-organising dynamics involved, it occurs at a non-verbal level although verbalisation adds value, mental models of task situations evolve and self-organise on the fly, and the internal utility structures of the tasks have an important effect on how these events might unfold. A decade later, there is finally a recognition that team mental models and situation awareness develop with experience and opportunities to adapt and interact (Chiappe, Strybel, and Vu 2015; Cooke et al. 2012, 2013; Gorman, Hessler et al. 2012; Likens et al. 2014). The latest developments in this area are expanding the concept of coordination to include synchronisation of body movements and neurocognitive events across people, and integrating the synchronisation levels with communication patterns (Guastello et al. 2016; Salas et al. 2015; Stevens et al. 2012, 2013; Stevens, Galloway, and Lamb 2014). Thus, to answer the central question, one can paraphrase an old piece of folk wisdom: If it looks like a paradigm, walks like a paradigm, and quacks like a paradigm, it is probably a paradigm.

Disclosure statement

No potential conflict of interest was reported by the author.

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