

Cognitive science as complexity science

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Abstract

It is uncontroversial to claim that cognitive science studies many complex phenomena. What is less acknowledged are the contradictions among many traditional commitments of its investigative approaches and the nature of cognitive systems. Consider, for example, methodological tensions that arise due to the fact that like most natural systems, cognitive systems are nonlinear; and yet, traditionally cognitive science has relied on linear statistical data analyses. Cognitive science as complexity science is offered as an interdisciplinary framework for the investigation of cognition that can dissolve such contradictions and tensions. Here, cognition is treated as exhibiting the following four key features: emergence, nonlinearity, self-organization, and universality. This framework integrates concepts, methods, and theories from such disciplines as systems theory, nonlinear dynamical systems theory, and synergetics. By adopting this approach, the cognitive sciences benefit from a common set of practices to investigate, explain, and understand cognition in its varied and complex forms.

This article is categorized under:

Computer Science > Neural Networks

Psychology > Theory and Methods

Philosophy > Foundations of Cognitive Science

Neuroscience > Cognition

KEY WORDS

complexity, emergence, nonlinearity, self-organization, universality

1 | INTRODUCTION

Cognitive science is the interdisciplinary study of cognition (i.e., mentality, mind, thinking, etc.), namely, mental faculties and intelligent behavior (Bermudez, 2014; Thagard, 2005, 2019). *Complexity science* is the interdisciplinary study of complex systems, which, as a starting definition, are phenomena composed of many interacting units that give rise to irreducible order at certain spatial and/or temporal scales (Érdi, 2008; Mitchell, 2009; Solomon & Shir, 2003). *Cognitive science as complexity science* is the interdisciplinary investigation of cognition understood as a complex system. This means applying concepts, methods, and theories from complexity science to phenomena typically researched by the cognitive sciences.

This article aims to make the following two points: a weaker point that the cognitive sciences benefit from incorporating the concepts, methods, and theories of complexity science; and a stronger point that many cognitive phenomena are properly treated as complex systems and, thus, ought to be investigated via complexity science. It will be made clear

that the weaker point is uncontroversial due to the fact that many features of complexity science are already employed by the cognitive sciences, for example, time-series analyses. The stronger claim is controversial in that it requires accepting a view of cognitive phenomena that is often at odds with many commitments of traditional cognitive science. It will be shown below that a complexity science-based investigative framework for the cognitive sciences includes understanding cognitive phenomena as exhibiting the following four features: *emergence*, *nonlinearity*, *self-organization*, and *universality*.

Like other biological and social sciences (Bar-Yam, 2016), the scientific study of cognition is becoming more like a big data enterprise. This is due in part to the ever-increasing amount of data being generated about the brain (Frégnac, 2017; National Science Foundation, 2011; Sporns, 2013) and the expanding inclusion of nonneural, cognitively relevant features of the body and world into the cognitive sciences (Allen & Friston, 2018; Anderson, 2014; Chemero, 2009; Favela, 2014; Thompson & Varela, 2001). Such a situation is making it more evident that various forms of cognition are complex systems. Consequently, it is crucial that accurate understanding and more complete explanations of cognition become guided by investigative frameworks based on complexity science.

In order to motivate these points, it helps to position complexity science in relation to other more mainstream scientific commitments. Accordingly, in the next two sections I explain what complexity science is and discuss its origins with a focus on the ways it juxtaposes with divergent commitments. After, I describe an investigative framework in which cognitive science is usefully cast as a complexity science (cf. Van Orden & Stephen, 2012). I then conclude by presenting examples of typical targets of research in traditional cognitive science that have been successfully investigated via complexity science.

2 | WHAT IS COMPLEXITY SCIENCE?

Complexity science is the interdisciplinary investigation of, and attempt to explain and understand, complex systems (Allen, 2001; Ball, Kolokoltsov, & MacKay, 2013; Érdi, 2008; Favela, 2015; Mobus & Kalton, 2015; Phelan, 2001; Vermeer, 2014). Complexity science has diverse origins (Figure 1), with early contributions from areas such as chaos theory, cybernetics, and Gestalt psychology, and more recently from big-data mining, network science, and systems biology (Castellani, 2018; Flood & Carson, 1993; Goldstein, 1999). As a result, complexity science serves as a point of integration from which a rich set of concepts, methods, and theories from previously disparate approaches can be successfully employed for various investigative and explanatory purposes. As an investigative framework, complexity science has been applied to phenomena studied in a variety of disciplines, including, but not limited to, biology, chemistry, economics, physics, and sociology (e.g., Boccara, 2010; Fuchs, 2013; Hooker, 2011a; Mainzer, 2007; Mitchell, 2009; Müller, Plath, Radons, & Fuchs, 2018). The cognitive, neural, and psychological sciences increasingly employ various aspects of complexity science (e.g., Favela, 2019a; Guastello, Koopmans, & Pincus, 2011; Sherblom, 2017; Sporns, Tononi, & Edelman, 2000; Tognoli & Kelso, 2014; Tomen, Herrmann, & Ernst, 2019; Tsuda, 2001). For example, concepts such as phase transitions (Wiltshire, Butner, & Fiore, 2018) and self-organization (Dale, Fusaroli, Duran, & Richardson, 2014) are utilized along with methods like agent-based modeling (Sayama, 2015) and time-series analyses (Riley & Van Orden, 2005), and then given theoretical grounding via theories such as

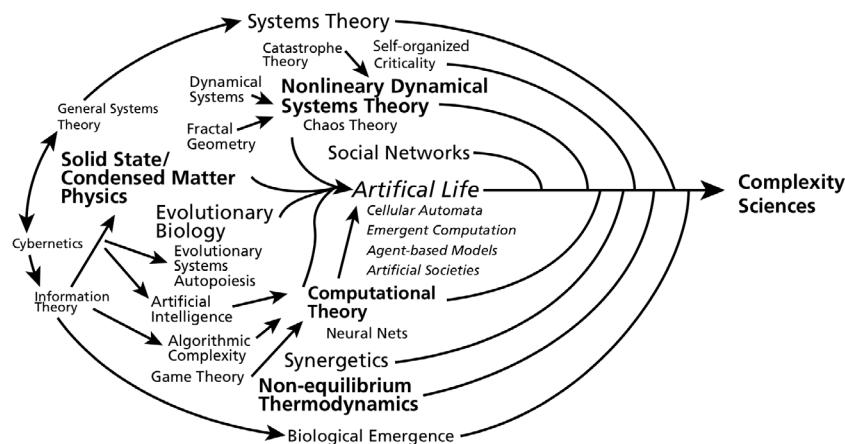


FIGURE 1 One way of viewing the diverse and rich foundations of complexity science. (Used with permission from Jeffrey Goldstein (1999))

catastrophe theory (Poston & Stewart, 1978) and universality classes (Timme et al., 2016). The increasing popularity of complexity science has stressed the need to answer the following question: Does the concept “complexity” refer to anything real; or, put another way, is “complexity” a scientific concept?

The short answer is yes, the concept “complexity” refers to something real. To begin a longer response, it is appropriate to understand “complexity” as an immature concept. In scientific practice, a concept is “immature” when although there is no broad agreement on its definition (cf. Kuhn, 1962), but there is enough family resemblance across its usages that practitioners have a general sense of what others mean when they use the word (cf. Wittgenstein, 1958). Across various literatures, the terms “complexity” and “complex systems” are utilized in assorted ways to refer to a range of characteristics. Bar-Yam (2016) focuses on such features as chaos, multiscale interactions, and universality as common to complex systems. Bishop and Silberstein (2019) list over a dozen properties often associated with complexity, with particular emphasis on feedback and strong nonlinearities. Érdi (2008) draws attention to three main characteristics: circular causality/feedback loops, small changes leading to “dramatic” effects, and emergence. Sporns (2007), following Herbert Simon, identifies three common features of complex systems: components, interactions, and emergence. Tranquillo (2019) discusses over two dozen sets of concepts, such as nonlinearity, self-organization, and simple rules leading to complex behaviors. Van Orden and Stephen (2012) discuss complexity in terms of its empirical signals, especially qualitative states that exhibit nonstationarity and phase transitions. A pessimistic take away from this small sample is that “complexity” refers to a hodgepodge of unrelated properties, which is evident by authors associating different terms with the word. This apparent lack of agreed upon characteristics has led some to question whether it is possible or not to give necessary and sufficient conditions for “complexity” (e.g., Ladyman, Lambert, & Wiesner, 2013), if alleged complex systems exist only relative to an observer (i.e., not really real; cf. Crutchfield, 1994), or if “complexity” is even a scientific concept (Taborsky, 2014). I think it is far too soon in the history of complexity science to draw these pessimistic conclusions.

Although there is some variation in the definition of “complexity” and the properties associated with complex systems, such reasons are not ground for abandoning complexity science. The fact of the matter is that complexity science is already practiced and complex systems are investigated in part or whole across the physical, life, and social sciences. In view of that state of affairs, it is not a moot point whether or not “complexity” or “complex system” are scientific concepts. Yet, it is reasonable to view those terms as being immature, namely, they are still developing and being refined. This is not an unusual situation in science. A number of core scientific concepts across various disciplines (e.g., cognition, gene, information, mole, etc.) are broadly applied without having necessary and sufficient definitional conditions. Moreover, such terms are open to revision even when it seems there was an accepted definition (e.g., the redefinition of the kilogram on May 20, 2019; Wood & Bettin, 2019). In that way, “complexity” and “complex system” are less like abstract and mathematical concepts (e.g., modus ponens, square, etc.) that can be defined via necessary and sufficient conditions and more like concepts in the natural and social sciences that are defined via family resemblance rather than strict conditions (e.g., mammal, nation, planet, etc.).

With that said, the remaining article asserts the following:

Complexity is not a mere metaphor or a nice way to put certain intriguing things, it is a phenomenon that is deeply rooted into the laws of nature, where systems involving large numbers of interacting subunits are ubiquitous. (Nicolis & Nicolis, 2007, pp. 2–3)

The aim of [investigating] Complexity is to express, explain and control the collective objects and phenomena emerging at a certain space-time scale from the simpler interactions of their components at a finer scale. (Solomon & Shir, 2003, p. 57)

From that perspective, and based on the various usages and descriptions of the terms mentioned above, complexity science can be understood as the scientific investigation of complex systems, which are typically characterized by the following four features: emergence, nonlinearity, self-organization, and universality. In an upcoming section, I articulate the ways these features are central to the investigation of cognition. But first, in the following section, I describe the state of scientific practice in the early- to mid-twentieth century that most influenced traditional cognitive science. After, I discuss key areas of research that ran contrary to those mainstream trends and that contributed to the ability of those four features to be scientifically investigated, which in turn play major roles in cognitive science practiced as complexity science.

3 | EARLY INFLUENCES ON COGNITIVE SCIENCE

It is not possible in a single section of an article to do justice to the history of cognitive science (for that, see Boden, 2006; Brook, 2007; Miller, 2003). But that is not my intention here. My aim is merely to highlight some of the key early influences on traditional cognitive science. The purpose in doing so is to then show in the following section how early influences on complexity science result in a cognitive science that holds diverging conceptual and theoretical commitments, and that those new commitments are necessary for successfully investigating cognition.

In line with Érdi (2008), to begin to understand the foundations of complexity science, it is helpful to recognize what approaches are standardly viewed as dominating the sciences of the early- to mid-twentieth century. Across the physical (e.g., particle physics) and life sciences (e.g., biology), various types of reductionism are typically seen as being central to scientific practice (Brigandt & Love, 2017). Ontological reductionism holds that a system is comprised only of its smallest constituent parts and their interactions, for example, a biological organism just is its molecules. Methodological reductionism holds that the best way to do science is to aim at investigating the lowest possible levels, for example, investigate the biochemical parts and processes of cells to best understand a plant. Epistemic reductionism holds that the knowledge of higher-level sciences can be reduced to lower-, more fundamental-level sciences, for example, psychology reduces to biology, which reduces to chemistry, which reduces to physics. In addition to reductionism, mechanistic approaches, with an emphasis on decomposition and localization, are also typically viewed as central to scientific practice (Craver, 2005).

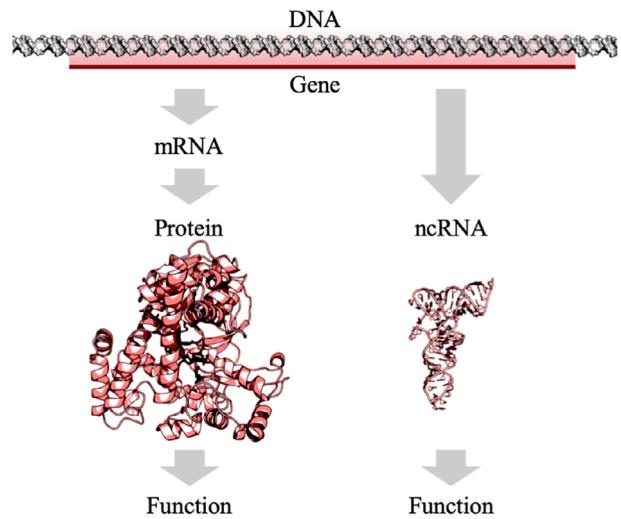
What is referred to as “mechanistic” approaches has varied over the history of science, with origins as early as Descartes, Galileo, and Newton (Glennan, 2017). Although there are various conceptions of mechanisms in contemporary philosophy (Glennan, 2017), two features can be generally agreed upon in terms of its role in twentieth century science. First, a mechanistic approach is not the same as reductionism (e.g., Craver & Tabery, 2019). Second, when mechanistic approaches were employed in scientific practice, it was typically as a methodological heuristic that aimed to explain a phenomenon by taking it apart, understanding the contributions its parts make, and identifying the steps of the processes that give rise to it. This was often done via decomposition and localization. As Bechtel and Richardson put it, decomposition allows for “the activity of a whole system [to be treated] as the product of a set of subordinate functions (Bechtel & Richardson, 1993/2010, p. 23). In this way, the whole is the sum of its parts, where their individual contributions to functioning are treated as additive and linear (Bechtel & Richardson, 1993/2010, p. 23). Localization is the investigative process by which “the different activities proposed in a task decomposition [are identified] with the behavior or capacities of specific components” (Bechtel & Richardson, 1993/2010, p. 26). By linking specific functions to individual components, localization is also compatible with the notion that individual contributions hold a linear relationship such that they can be added together to understand the functioning of a system, even if there are feedback loops.

Scientific practice in the early- to mid-twentieth century guided by reductionistic (especially methodological) and mechanistic commitments undoubtedly facilitated many advances. In biology, for example, one of the greatest discoveries was the structure of DNA and subsequent research aimed at drawing connections between genes and function (Figure 2). In light of such successes, especially in the biological sciences, it is no wonder that reductionist and mechanistic approaches greatly outshined many of the perceived alternatives at the time, such as holism (Gatherer, 2010; Mazzocchi, 2012).

Although the biological sciences exemplified investigative frameworks guided by assumptions such decomposability, linear relationships, and methodological reductionism, those commitments also played foundational roles during cognitive science's formative years. From early work by Chomsky (1957/2002) in linguistics and Fodor (1983) on modularity, early cognitive science treated the mind as a collection of faculties (cf. McDermott, 2001), for example, decision-making, language, problem-solving, visual perception, etc. Accordingly, the cognitive scientist's (and cognitive psychologist's) job was to identify the various cognitive faculties (Boden, 2006; Fodor, 1980), or “mechanisms” (McDermott, 2001). Until the 1980s or so, cognitive science focused on revealing cognitive mechanisms in the form of rules of thought, which kept their work mostly autonomous from research on the physical instantiation of those rules and thoughts (e.g., connectionist and neuronal networks). Accordingly, cognitive science was not very reductionistic. Two things changed this.

The first was owed to Marr (1982) and his three levels investigative framework (Figure 3). The first two levels were very much consistent with the typical cognitive psychologist approach championed by folks like Fodor: identify the “why” of the cognitive act you are investigating (i.e., computational theory; e.g., “why does problem-solving work that way?”); and then figure out the rules that manipulate the representations involved in that act (i.e., representation and algorithm; e.g., the steps involved in solving problems). The third part of the framework is what distinguished Marr from those who viewed cognitive psychology as unconcerned with “lower level” sciences and opened the way towards

FIGURE 2 An organism's functions as the product of a linear causal pathway that begins with DNA. Research in the biological sciences during the early- to mid-twentieth century exemplified such reductionist and mechanistic commitments. (Adapted from Shaffee (2015). CC BY 4.0)



incorporating neuroscience research, namely, figuring out how the representation and algorithm is physically realized (i.e., hardware implementation). This part allowed cognitive psychologists to attempt to build bridges between their research and that of neuroscientists, who were at the time (ca. 1990s) developing neural imaging tools, such as functional magnetic resonance imaging (fMRI). In this way, cognitive science incorporated reductionism as identifying where in the brain various cognitive capacities were localized and decomposing one capacity from another became central research goals.

Of course, even as a summary, this historical narrative paints in broad strokes. Moreover, it makes it seem as if cognitive science has followed a single trajectory, one that is readily confirmed by many cognitive science textbooks and resources (e.g., Abrahamsen & Bechtel, 2012; Bermudez, 2014; Boden, 2006; Thagard, 2005). With that said, what Kuhn was surely right about was that the history of science does not demonstrate a single, smooth, and upward progression, where more advanced sciences build on top of their predecessors (Kuhn, 1962). But, contrary to Kuhn, history also does not demonstrate radical shifts to single dominant paradigms either. Consequently, although reductionist and mechanistic approaches surely produced many great accomplishments, it is clear that other investigative frameworks were making advancements as well. Moreover, those other approaches did so in ways often incongruous with reductionist and mechanist methodological and theoretical commitments. In the biological sciences, systems-focused biology, such as developmental systems theory (e.g., Oyama, 2000), were practiced simultaneously with molecular biology. In the physical sciences, research on the thermodynamics of open systems (including living organisms) were practiced simultaneously with classical thermodynamics research on closed and isolated systems (e.g., theory of dissipative structures; Prigogine & Lefever, 1973). In the psychological sciences, non-computational and non-representational frameworks like ecological psychology, were practiced simultaneously with cognitive psychology (Chemero, 2013). In the next section, I discuss three of the core contributors to contemporary complexity science: systems theory, nonlinear dynamical systems theory, and synergetics. These three predecessors are emphasized because they have made progress on the key topics of emergence, nonlinearity, self-organization, and universality, which provide the fundamental basis for cognitive science as complexity science.

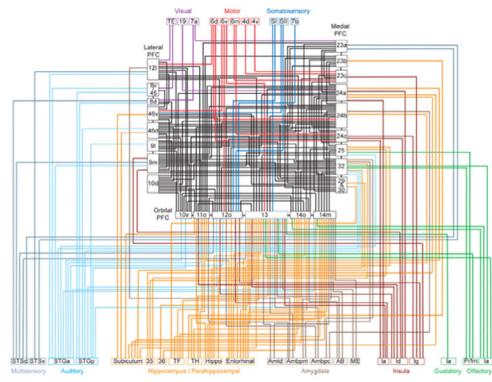
4 | KEY CONTRIBUTORS TO COMPLEXITY SCIENCE

As mentioned above, there are a range of disciplines—such as chaos theory, cybernetics, and Gestalt psychology—that have contributed to the development of complexity science as it is understood today (Figure 1). Various authors have drawn attention to disciplines they take as central to complexity science, often for reasons related to their particular area of interest, such as biology or physics (Baofu, 2007; Bar-Yam, 2016; Érdi, 2008; Hooker, 2011b; Tranquillo, 2019). In that spirit, I draw attention to the three areas that I believe contribute the most to understanding cognitive science as complexity science: systems theory, nonlinear dynamical systems theory, and synergetics. Understanding these three areas makes it apparent why emergence, nonlinearity, self-organization, and universality are crucial to investigating and explaining cognitive phenomena as complex systems. Moreover, in doing so, it becomes evident how a cognitive science cast as complexity science diverges from the typical commitments of traditional cognitive science.

Computational Theory



Representation and Algorithm



Hardware Implementation

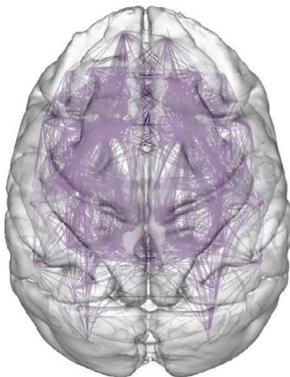


FIGURE 3 Marr's three levels of analysis (Marr, 1982). *Computational theory*: What is the computation; what is it for? Typically, this is the phenomenon of interest, such as problem-solving, for example, how to crack open a nut. (Modified from Falótico (2015). CC BY-SA 4.0). *Representation and algorithm*: How is the computation implemented; what are the inputs and outputs that manipulate representations? For example, a connectivity diagram of a macaque monkey's brain displaying decision-making networks connected with limbic, motor, and sensory systems. (Reprinted with permission from Averbeck and Seo (2008). Copyright 2008 Public Library of Science; CC BY 4.0). *Hardware implementation*: How are the algorithms and representations physically realized, for example, the structural connections of a macaque monkey's neuronal networks. (Reprinted with permission from Goulas et al. (2014). Copyright 2014 Public Library of Science; CC BY 4.0)

4.1 | Systems theory

Here, “systems theory” is an umbrella term that encompasses such concepts and theories as cybernetics (Wiener, 1948) and general systems theory (e.g., von Bertalanffy, 1972; cf. Hammond, 2003). At its most general, systems theory centers on the study of abstract organizational principles (Heylighen & Joslyn, 1999). Modern-day thinking about systems theory tends to begin with von Bertalanffy, who argued that because systems—especially biological—interact with and are open to the influence of their environments, they cannot be understood via reduction to their constituent parts. Rather, systems are wholes that emerge from the interaction of their parts. In that way, a plant cannot be defined by its cells and biochemical processes, but by the interactions of its cells, organs, body, and environment. Like von Bertalanffy's general systems theory, cybernetics also emphasized system-level activity. However, cybernetics, which originated with Wiener, was particularly focused on the ways systems communicate and manipulate information (Adams, 1999). Central to cybernetics is the study of feedback and feedforward processes, especially for purposes of control. Biological and artificial systems can be cybernetic, in that both involve feedback and feedforward in order to maintain homeostasis (e.g., a mammal's body temperature) and specified state maintenance (e.g., room temperature via thermostat). It is evident a central contribution of systems theory to complexity science was a focus on irreducible system-level activity, component interactions as central to accounting for a phenomenon of interest as opposed to the components themselves, and feedback.

4.2 | Nonlinear dynamical systems theory

The majority of systems are dynamic, such that their behavior changes over time. Dynamical systems theory (DST) applies mathematical tools to evaluate the variation and stability of dynamic systems. DST is commonly applied by assessing and accounting for variables via sets of differential equations and then plotting activity in a phase space in order to show the possible states of the system as it evolves over time. Phase space plots also allow the researcher to see how variables interact and how the whole system transitions between qualitatively different states. Though DST applies to linear phenomena, much of the appeal and strength of its methods centers on its ability to account for nonlinear phenomena, namely, nonlinear dynamical systems theory (NDST). An activity is nonlinear when its outputs are not proportional to its inputs. This can be due to exponential and multiplicative interactions among parts (Enns, 2010), which, in turn, can give rise to unexpected shifts among qualitatively distinct, yet stable, behaviors. In addition, the parts of nonlinear systems cannot be decoupled (Fuchs, 2013, p. 13). If, for example, a system is comprised of two parts that interact nonlinearly, then neither part can be understood separate from the other, as changes to one part has effects on the other. Attempting to do so, such as solving one part of a model in isolation, would eliminate the system-level dynamics. Consider the following example of coupled differential equations:

$$\dot{x} = ax \times by,$$

$$\dot{y} = cx \times dy.$$

If the equations could be solved in isolation from each other, that is, if changes to x do not require accounting for changes to y , then the above equations would refer to two, separate one-dimensional equations. But if the equations could not be solved in isolation from each other, that is, if changes to x requires taking into account changes to y , then the above equations would refer to a single, nondecomposable two-dimensional system (Favela & Chemero, 2016; Fuchs, 2013). This simple example makes clear how NDST provides numerous tools for studying system-level behavior. Three other facets of NDST are especially important to the practice of cognitive science as complexity science that is discussed below.

First, the application of NDST as a set of methods and research strategy tends to aim at identifying the rules (or laws) that govern how a system's state evolves over time (Riley & Holden, 2012). Such rules are presented via differential equations, or the governing equations of a system (Bongard & Lipson, 2007; Brunton, Proctor, & Kutz, 2016; Dale & Bhat, 2018; Daniels & Nemenman, 2015). Limit cycles are examples of such rules captured by differential equations. A limit cycle is a dynamical system with a closed trajectory (Strogatz, 2015). However, differential equations will not alone provide comprehension. This is because some differential equations cannot be solved analytically, especially when, as discussed above, multiple equations are coupled. Accordingly, in order to more fully comprehend a system's dynamics, computer simulations and phase space plots are utilized. Where differential equations provide quantitative accounts of a target phenomenon, simulations and plots provide qualitative accounts that facilitate researcher comprehension in a way the former methods alone do not. A simple, yet illustrative, example of this is a DST account of pendulum dynamics. The quantitative part of the account is provided via the following differential equation:

$$\frac{d^2\theta}{dt^2} + \frac{g}{l} \sin \theta = 0.$$

Although somebody who is familiar with differential equations, but not necessarily this pendulum model, may have a sense of what is going on—for example, that the system involves angular displacement (θ) of part (l) that is acted upon by gravity (g)—they likely do not have comprehension of the qualitative aspect of the system. For that, the differential equation needs to be plotted (Figure 4) and potentially simulated (for an example of a simulation of a pendulum in movement based on this differential equation see https://en.wikipedia.org/wiki/File:Oscillating_pendulum.gif).

A second key feature of NDST adopted by complexity science is a focus on sudden and unexpected qualitative shifts common to nonlinear dynamical systems, referred to as phase transitions. NDST provides various tools for understanding phase transitions of systems, for example, by identifying universal patterns known as catastrophe flags (Isnard & Zeeman, 1976; Poston & Stewart, 1978). Eight catastrophe flags have been identified: anomalous variation, critical slowing down, divergence, divergence of linear response, hysteresis, inaccessibility, (multi)modality, and sudden jumps (Gilmore, 1981). They are characteristics of nonlinear dynamical systems that can be observed at system-level activity. To empirically observe a catastrophe flags near a qualitative phase shift is typically a strong indicator that a

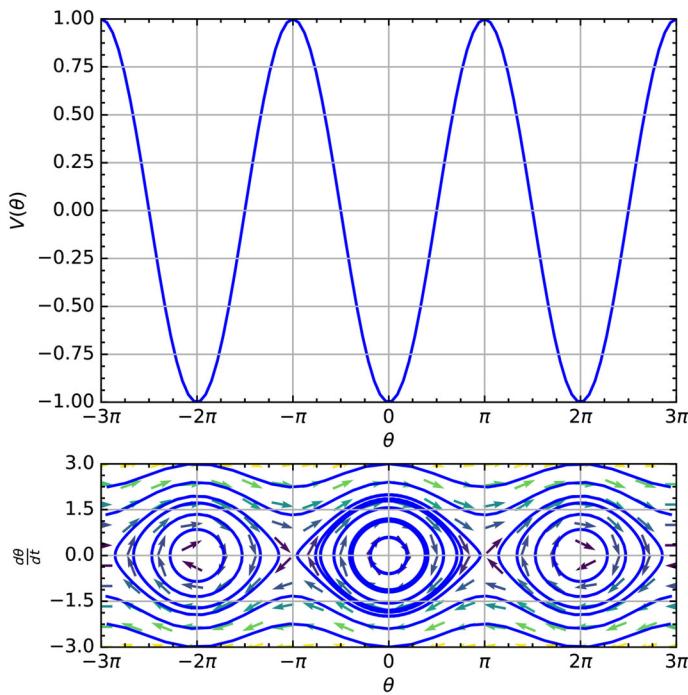


FIGURE 4 Plots of pendulum dynamics. Time-series plot of pendulum differential equation (top). Phase space plot of pendulum differential equation (bottom). (Reprinted with permission from Krishnavedala (2014). CC BY-SA 4.0.)

phenomenon is a nonlinear system. A broad range of human behavioral changes have demonstrated catastrophe flags, especially hysteresis. The most widespread application of NDST via catastrophe flags in human research is to human development (e.g., Thelen & Smith, 2006; van Geert, 1994) and action/perception (e.g., Haken, Kelso, & Bunz, 1985; Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007; van Rooij, Favela, Malone, & Richardson, 2013).

A third area of NDST that has come to prove central to complexity science is fractal geometry, as well as methods for its assessment. Originating with Mandelbrot in the 1970s (Mandelbrot, 1977), a fractal is a scale-free, self-similar structure. “Scale-free” refers to exact or statistically self-similar patterns or structures at various spatial and temporal scales. Fractals can occur spatially or temporally, such that the global structure is maintained at various scales of observation (Figure 5). Spatial fractals that are exactly self-similar include Koch and Sierpinski triangles. Spatial fractals that are statistically self-similar include geographic phenomena such as coastlines and mountain ranges, as well as biological phenomena such as tree branching and cauliflower. Temporal fractal structures that are exactly self-similar include metronomes and radio frequencies. Temporal fractal structures that are statistically self-similar include finger tapping (Kello, Beltz, Holden, & Van Orden, 2007), healthy heartbeats (Peng et al., 1995), healthy human gait patterns (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995), spontaneous single-neuron activity (Favela, Coey, Griff, & Richardson, 2016), and changes in fMRI signals (Lee et al., 2008).

As the above examples demonstrate, fractals are ubiquitous in nature. As such, it is surprising that it was not until the 1970s that such structures were titled. That is remarkable in itself. But what are more fascinating are the mathematical developments that followed. Mandelbrot hit the nail on the head when he stated, “Clouds are not spheres, mountains are not cones, coastlines are not circles, and bark is not smooth, nor does lightning travel in a straight line” (Mandelbrot, 1977, p. 1). The truth underlying that statement has caused some to say that for those natural phenomena, it is meaningless to utilize traditional mathematical concepts and methods to assess them (Falconer, 2013). It is “meaningless” in that it is quite uninformative when the details of such phenomena are smoothed over—pun intended: clouds are not smooth spheres. As a result, new mathematical tools have been developed—and some old ones have been applied in new ways (e.g., set theory; Brown & Liebovitch, 2010)—in order to assess such phenomena in meaningful ways. For example, Figure 5 depicts three types of time-series data: white (random, unstructured), pink (self-similar, structured), and brown (random and unstructured at shorter timescales, more structured at longer timescales). If all three data sets were analyzed via standard traditional cognitive science methods (e.g., assessing for the mean), and if the mean time is the same for all three, then a researcher could be led to believe the behavior that produced each was the same. However, if nonstandard methods (e.g., fractal analysis) were used for all three data sets, then, even if the mean is the same, the researcher would see that the behaviors that produced the data were quite different. For example, during a visual-search task (e.g., Aks,

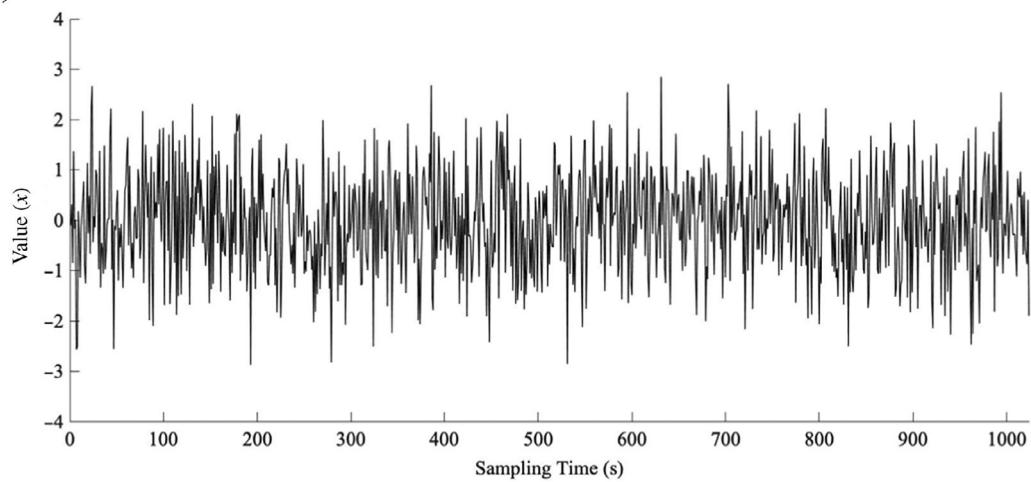
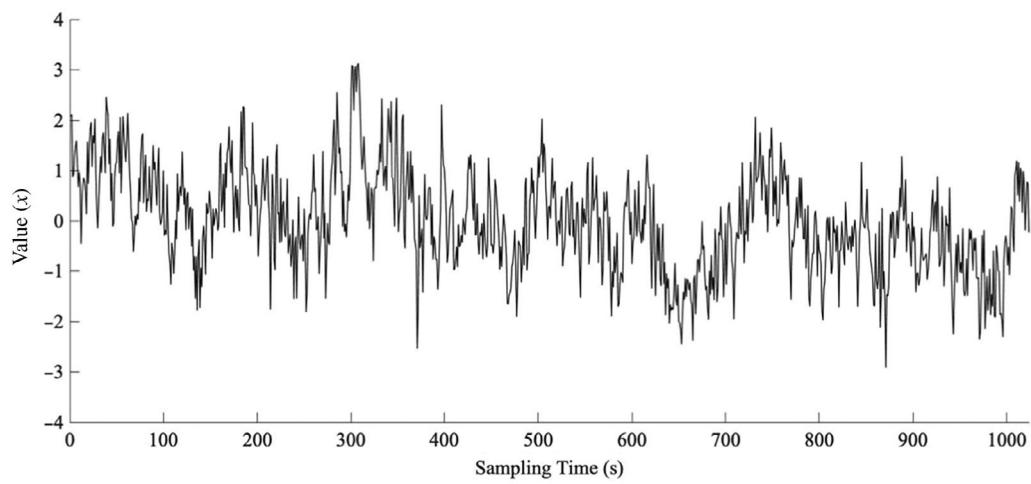
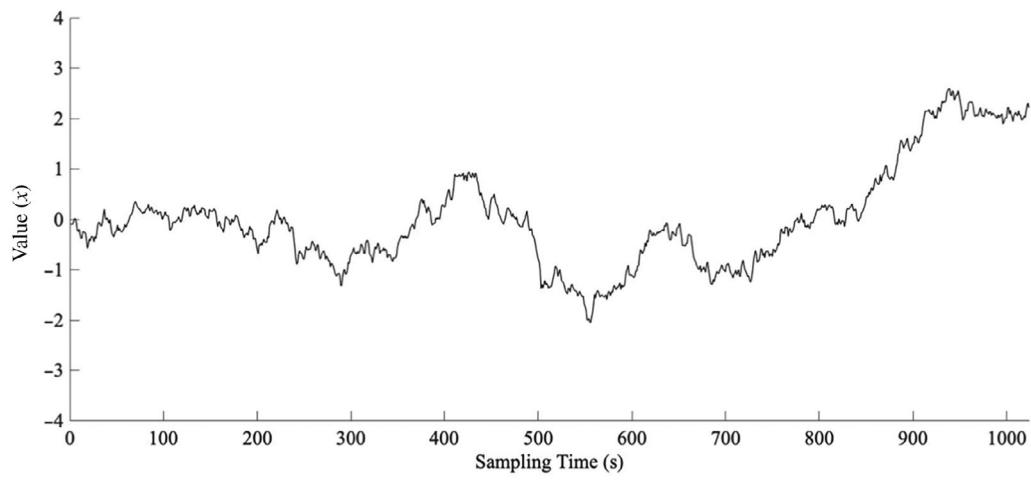
(a) White noise**(b) Pink noise****(c) Brown noise**

FIGURE 5 Three time-series signal structures: white, pink, and brown. The Y-axis refers to a value (x) such as eye movements, finger taps, or heartbeats. The X-axis refers to temporal values (s) such as milliseconds or seconds. (a) Random white noise, which is unstructured over time. (b) Pink noise (also known as $1/f$ noise or $1/f$ scaling) is fractal in structure, specifically, the signal's structure is self-similar at shorter and longer timescales. (c) Brown noise, which exhibits random structure at shorter timescales and more ordered structure at longer timescales, such that it is not as unordered as white noise but not as ordered as pink noise (figure created by Mary Jean Amon)

Zelinsky, & Sprott, 2002), white could have been produced by a participant inefficiently looking at random locations on a screen, pink produced by a participant utilizing an efficient strategy, and brown by a participant whose visual-search patterns were sometimes efficient and sometimes not.

The following lists methods commonly used to assess for fractals and self-similarity: box/grid counting (Mandelbrot, 1977), detrended fluctuation analysis (Peng et al., 1995), multifractal analysis (Kelty-Stephen & Wallot, 2017), multifractal detrended fluctuation analysis (Ihlen, 2012), spectral analyses (e.g., Fourier transform and periodogram; Delignieres et al., 2006; Sebastián & Navascués, 2008), and wavelets (Ihlen & Vereijken, 2010). These methods have given researchers the quantitative tools needed to assess and reveal features of natural phenomena not previously or properly comprehensible. Most noteworthy for present purposes, these methods have been employed in the assessment of complex systems. Specifically, they have been applied in the assessment of historical variation, interaction-dominant dynamics, nonlinearity, and scale-free structure.

4.3 | Synergetics

The third contributor to complexity science that has had a large influence on cognitive science is synergetics. Synergetics is an interdisciplinary field in itself that investigates systems with many parts that interact at various spatial and temporal scales (Haken, 2007). A number of features distinguish synergetics from other frameworks that investigate system-level phenomena. First, it focuses on spontaneous processes and structures, specifically, self-organization. Second, its aim is to, “*unearth general principles (or laws) underlying self-organization irrespective of the nature of the individual parts of the considered systems*” (Haken, 2016, p. 150; italics in original). In other words, a primary goal of synergetics is to discover general laws of the ways systems self-organize. Third, it conceptualizes systems in terms of macro- and microscopic spatial and temporal scales in a contextual manner. Specifically, there is no absolute “macro-” scale that applies to all investigations; what counts as “macro-” and “microscopic” depends on the research question. This leads to the fourth and final distinguishing feature of synergetics: research is guided by the conceptualization and application of order and control parameters.

As discussed above, NDST-guided research often centers on identifying how a system's state evolves according to a rule. Mathematics, in the form of differential equations, is typically employed to this end. Similarly, synergetics is interested in discovering general laws of self-organization. Moreover, such laws are stated in terms of differential equations that capture the macroscopic state of a system. Within synergetics, such macroscopic states are referred to as order parameters (Haken, 1988, p. 13). *Order parameters* are the collective variable that describes the macroscopic phenomenon under investigation (Haken, 2016, p. 151). The other half of the approach are the control parameters. *Control parameters* are those variables that guide the system's dynamics, such as energy or information that flows into and through the system and/or among its parts. At this point it is crucial not to make the following mistake: Although it is reasonable—for example, in terms of the experimental design stage—to conceptualize the order parameter like a dependent variable and the control parameters like independent variables (cf. Robertson, 1993), the comparison is not one of equivalency. The crucial difference manifests in the way each set treats causation. In terms of dependent and independent variables, the latter causes the former. In terms of order and control parameters, the latter does not cause the former. Control variables do not cause the system-level behavior as a result of any sort of linear cause–effect relationship (cf. Kelso, 1997, pp. 7, 45). This is due to two commitments in synergetics: the (unfortunately labeled) slaving principle and circular causality (Haken, 2016).

The slaving principle refers to the idea that the order parameter determines the activity of the system's parts (Haken, 1988, pp. 13, 48). Note that the slaving principle is not the idea that the order parameter determines the control parameters. This significant difference leads into the second commitment: circular causation. An example is helpful when trying to understand what circular causality means in synergetics. Consider the Haken–Kelso–Bunz (HKB; Haken et al., 1985) model of bimanual coordination. This model was an early achievement in synergetics that aimed to explain the dynamics and transitions among states while two limbs moved at different frequencies; here the limbs were the index fingers with movements starting at in-phase or anti-phase positions. The goal was to account for the observed patterns of behavior with as few variables as possible. In terms of the synergetics framework, the order parameter is the variable that captures the coordinative states of the two fingers, and the control parameter is the variable that captures what is driving the coordinative states. The concise (and now influential) model that was developed is as follows:

$$\dot{\phi} = -a \sin \phi - 2b \sin 2\phi$$

Here, the order parameter is $\dot{\phi}$, which refers to the dynamics over time, and the control parameters are a , the frequency of finger 1, and b , the frequency of finger 2. With this simple model, the entire range of coordinative movements is accounted for. In terms of the slaving principle, neither a nor b cause $\dot{\phi}$, because they are enslaved to $\dot{\phi}$. That is to say, that while a and b do effect $\dot{\phi}$, $\dot{\phi}$ also effects a and b . In that way, there is circular causality: none of the variables can be pinpointed as the starting point in a linear causal chain to explain the system-level (i.e., macroscopic) dynamics. The manner in which circular causation occurs here is also the manner in which nonlinearity is exhibited. For one reason, control parameters do not have an additive or linear effect on the order parameter, such that increasing control parameter a by one unit will not necessarily result in the order parameter $\dot{\phi}$ exhibiting a proportional effect.

The order and control parameter approach has proven quite successful. As a modeling strategy, it has facilitated the identification of phase transitions among various behaviors. Examples include such diverse cases as decision-making (van Rooij et al., 2013), speech categorization patterns (Tuller, Case, Ding, & Kelso, 1994), perception of ambiguous figures (Ditzinger & Haken, 1995), and synergies among neuronal ensembles (Kelso, 2012). As a part of an explanatory framework, it has facilitated the identification of “laws” of self-organization, often in line with catastrophe theory. Examples include critical slowing down (Scholz, Kelso, & Schöner, 1987), hysteresis (Haken et al., 1985; van Rooij et al., 2013), multistability (Ditzinger & Haken, 1995), and sudden jumps (Thelen & Smith, 2006).

Taken together, systems theory, NDST, and synergetics have made major contributions to complexity science. They have provided sophisticated conceptual tools to understand complex systems. Moreover, they have provided methods to empirically assess those concepts. With this background in place, in the next section I present the cognitive science as complexity science investigative framework.

5 | COGNITIVE SCIENCE AS COMPLEXITY SCIENCE

The aim of this section is to explain the central concepts and theories of cognitive science as complexity science (CSCS) and methods for assessing them. After, I provide an outline for putting the framework into practice. The section then concludes by reviewing complexity science-based research on topics typically central to traditional cognitive science.

5.1 | Key concepts and methods for investigation

As discussed above, various authors highlight aspects of complexity science that interests them most, which can lead some to believe there is no coherent discipline that investigates complex systems. Although I am sympathetic to the idea that complexity science is an immature science, I do think there are core concepts that capture the central features of specific domains of interest. Accordingly, the following four concepts are crucial for understanding cognitive phenomena as complex systems: emergence, nonlinearity, self-organization, and universality.

The first concept is *emergence*. Emergence is one of the most common concepts associated with complexity science (e.g., Érdi, 2008; Favela, 2019a; Sporns, 2007), with some claiming it is equivalent to complexity or at least essentially intertwined (e.g., Agazzi & Montecucco, 2002). In some sense that captures the idea that the whole is more than the sum of its parts, each of the key predecessors to CSCS have attempted to account for emergence. For example, central to systems theory was the attempt to understand systems as wholes that result from interactions of their parts and not reducible to what the parts do in isolation. For reasons that will be stated shortly, I argue that emergence of the type typical to the study of cognition is often cashed out in terms of interaction-dominant dynamics.

While I respect the fact that there is an enormous literature on emergence (e.g., Bedau & Humphreys, 2008; Goldstein, 1999; Kim, 2006), I will attempt to provide a concise sense in which it plays a role in CSCS. In the philosophical literature, five features commonly considered necessary for emergence: downward causal influence, novelty, relationality, supervenience, and unpredictability (Francescotti, 2007). The scientific literature, however, typically does not use “emergence” to refer to all of those five features. As Favela (2019b) has argued, in the CSCS-relevant literature, “emergence” is often used interchangeably with “interaction-dominant dynamics” (e.g., Davis, Brooks, & Dixon, 2016; Holden, Van Orden, & Turvey, 2009; Szary, Dale, Kello, & Rhodes, 2015; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009). Given traditional cognitive sciences’ (TCS) focus on reductionism and

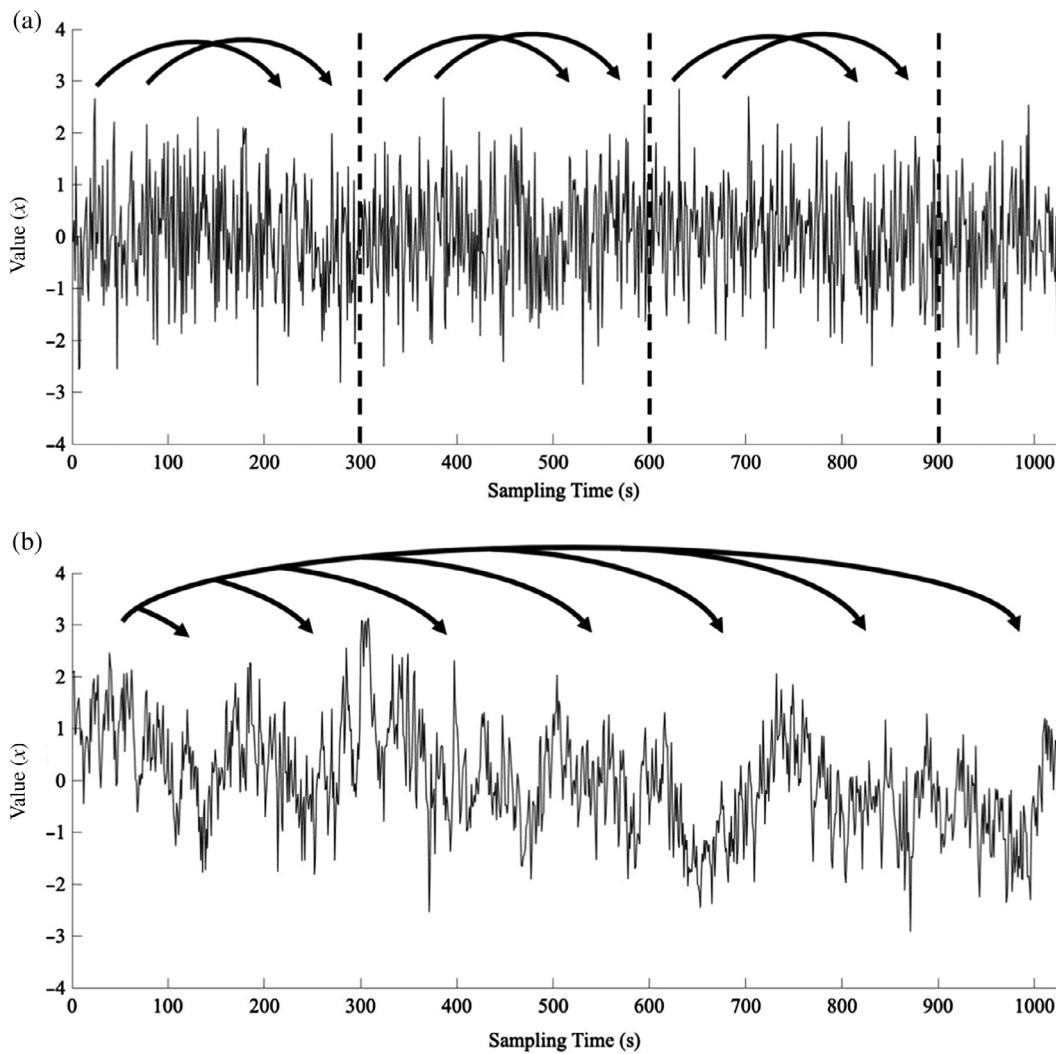


FIGURE 6 Component-dominant dynamics and interaction-dominant dynamics. (a) A synthetic white noise time-series. Each section depicts the localized effect of perturbations common to systems exhibiting component-dominant dynamics. (b) A synthetic pink noise ($1/f$ scaling) time-series. The arrows depict the distributed, nonlocalized effects of perturbations common to scale-free systems exhibiting interaction-dominant dynamics. (Image inspired by Davis et al., 2016)

mechanisms, the type of dynamics more commonly observed in TCS-based frameworks are component-dominant dynamics. A system's dynamics are component-dominant when the system-level dynamics are reducible to the additive and linear relationship of the dynamics the components have if separated and added together (Figure 6a). Component dominance is a common assumption of much TCS and is exhibited by the method of decomposition and localization discussed above. A system's dynamics are interaction-dominant when they exhibit nonlinear feedback among the interactions of their parts, such that it is the continual interactions of the parts that facilitate the system-level dynamics (Figure 6b). As with synergetics, the causation here is one of circularity: the system-level dynamics and the parts simultaneously structure each other's dynamics. Like cybernetics, feedback is crucial in interaction-dominant systems. However, unlike cybernetics, the feedback is not in the service of prescribed outcomes for purposes of control. As complex systems, interaction-dominant systems are context-dependent such that varying contexts can alter the nature of the parts during interactions. In the complexity science literature, there are many tools for assessing emergence, with computational models doing much of the work (e.g., agent-based models and cellular automaton; Floreano & Mattiussi, 2008). If, however, Favela (2019b) is correct, and emergence in CSCS is always a kind of interaction-dominant dynamics, then many of the same tools that evaluate interaction dominance ought to be applicable to the investigation of emergence; thereby resulting in emergence being an empirically tractable phenomenon.

The second concept is *nonlinearity*. Like emergence, nonlinearity is quite commonly referred to in the complexity science literature as a key feature of complex systems (e.g., Bishop & Silberstein, 2019; Tranquillo, 2019). It has also (obviously) been central to NDST, but also synergetics, especially in regard to the slaving principle and circular causality exhibited by the relationship among order and control parameters. I have already pointed out some of the features of nonlinearity above, but that was primarily in the service of explaining methods. Here I focus a bit more on the definition. Though nonlinearity can be defined simply, the consequences for a system that exhibits it are more complicated. Nonlinearity refers to cases when the output is not directly proportional to the input. Instead, outputs are exponential or multiplicative. In contrast, linearity refers to cases when the output is proportional to the input, such that outputs are the additive result of the inputs. Assuming that a system or data set is linear or nonlinear has numerous consequences for research, two of which I draw attention to here. The first centers on the distinction between historical and logical variation. *Historical variation* refers to the notion that fluctuations in a system are influenced by its previous states (Klein, 1997). This type of variation contrasts with *logical variation*, the central underlying assumption of most data analysis methods used in TCS. Methods such as standard linear statistics (e.g., analysis of variance and *t* tests) treat differences between measurements as discreet from each other, such that variation is not influenced by history. In this way, given enough observations (e.g., coin tosses, dice rolls, etc.) measurements will adhere to the central limit theorem and fall along a Gaussian distribution. There is no doubt that linear statistics are useful when assessing all sorts of phenomena. However, when it comes to complex systems where historical variation is the rule and not the exception (May, 1976), reliance on methods that are ahistorical regarding their data will surely result in distorted or false conclusions. Remember, linearity underlies logical variation in that it is assumed that enough data points will fall along a Gaussian bell-shaped distribution. Allowing for historical variation in a system does not make the same assumption that enough data points will adhere to Gaussian distribution. If previous states effect current and future states of a system, then it is not guaranteed how the data will be structured. TCS, with its usage of standard linear statistics (including Bayesian; Favela & Amon, forthcoming), does not account for nonlinear features of complex systems, such as hysteresis.

It is worth noting that there is no single kind of data analysis that will make a definitive case for a data set exhibiting historical variation. Assessing for power-law distributions, for example, is often a first-step in investigating whether a system exhibits historical variation. Yet, evidence of power laws alone will not arbitrate the issue as there are many thorny issues involving the relationship of fractals, historical variation, normal distributions, and power laws. With that said, analyses such as the cocktail model (Holden et al., 2009), which express distributional features of data (e.g., location, scale, and shape; Amon & Holden, 2019), can contribute to building a case as to whether or not historical variation is at play in a particular phenomenon. In the case of neuronal activity, for example, since no single measure has yet to be developed that can determine whether a data set exhibits complexity, Marshall et al. (2016) provide a data toolset that involves applying maximum-likelihood estimations to four types of distributions (power law, doubly truncated power law, exponential, and log normal) in data sets. Again, no single analysis is available to determine such features as historical variation or complexity, but cases can be motivated via methods such as cocktail models and maximum-likelihood estimations.

The second consequence concerns the manner in which system perturbations are assessed. If a system's dynamics are the result of linear (i.e., additive) processes, then it follows that the effects of perturbations will be localized in its individual components (Holden et al., 2009, p. 319). This is because linear systems have little-to-no interactions, such that the system-level dynamics are the result of additive relationships among its relatively independent parts (Figure 6a). On the other hand, if a system's dynamics are the result of nonlinear (e.g., multiplicative) processes, then it follows that the effects of perturbations will not be localized and will percolate throughout the system due to interaction-dominant dynamics (Figure 6b). There are many methods for assessing nonlinearity and the relationship among component parts, including recurrence quantification analysis (RQA; Coco & Dale, 2014; Shockley, 2005; Figure 7). In the context of complex systems, RQA identifies recurrent patterns of behavior that unfold over time and are visualized in a recurrence matrix (Webber & Zbilut, 2005). Recurrence plots can be used to visualize the recurrence of single features of a system, such as various wave heights of a body of water (Webber & Zbilut, 2005), or various parts of a single system, such as wave heights and overall depth of a body of water. The left plot in Figure 7 depicts simulated data from an experiment. The right plot depicts in greater detail the circled part of the left plot. By color coding data points—that is, red for α , green for β , and blue for γ —a recurrence plot is able to decipher between qualitative shifts in behavior, where each color represents a distinct and repetitive pattern that unfolds over time. Taken together with quantitative tools, the recurrence plot can reveal the nonlinear effects that, for example, multiple participants during a task or specific actions have on each other as they contribute to a single task.

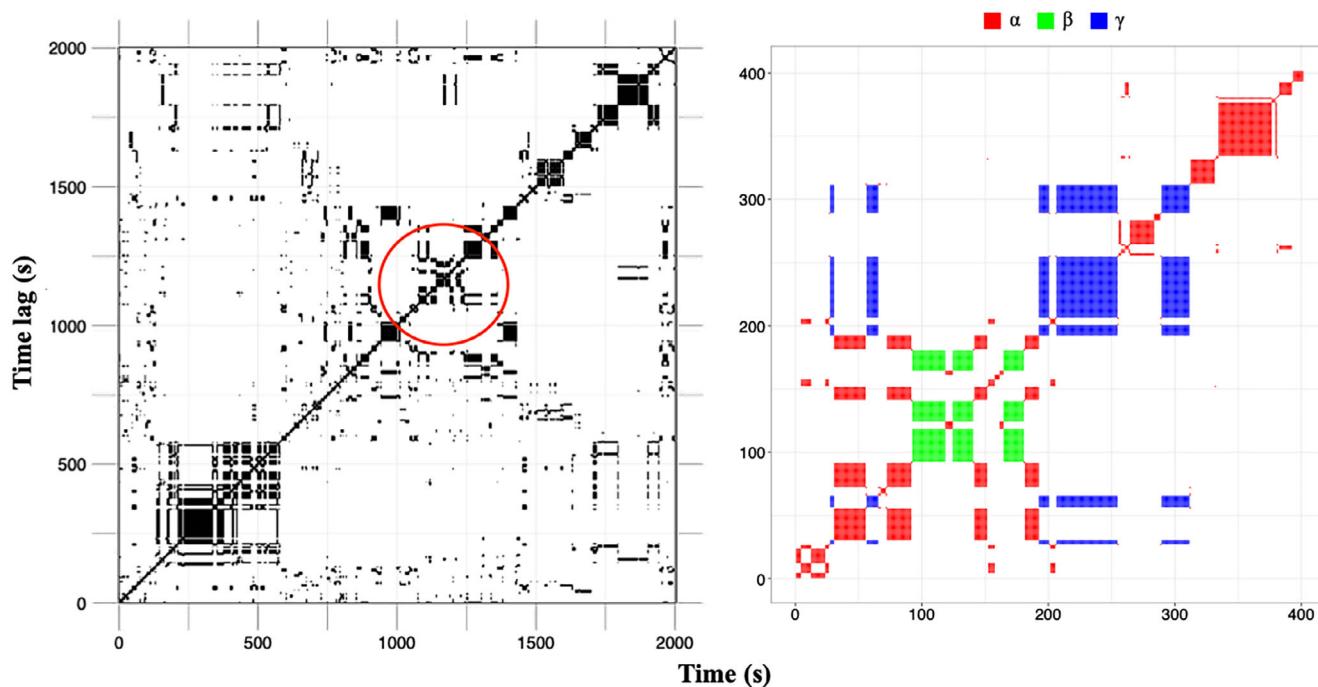


FIGURE 7 Recurrence quantification analysis plots. The left plot depicts the recurrence of events across 2000 s. The right plot depicts in greater detail the circled part of the left plot. By color coding data points—that is, red for α , green for β , and blue for γ —a recurrence plot is able to decipher between qualitative shifts in behavior, where each color represents a distinct and repetitive pattern that unfolds over time. (Figure created by Hana Vrzakova based on code and data from Coco & Dale, 2014)

The third concept is *self-organization*. Self-organization was first introduced above in discussions of systems theory and synergetics. Systems theory diverged from cybernetics due to the former's focus on predefined or prespecified outcomes of systems with feedback. On the other hand, systems theory was interested in systems that organized without direct intervention or instruction from an outside source or central controller. Synergetics took the topic a step further and explored general rules that resulted in self-organized behavior. Like fractals, self-organization seems to be ubiquitous in nature. Examples of the self-organization of complex structures and activity range from Benard-Rayleigh convection cells in heated fluids and Belousov-Zhabotinsky chemical reactions, to fish bait balls and starling murmurations.

Following from the influences of systems theory and synergetics, self-organization plays a very specific role in CSCS, which can be summed up by the following two questions: First, can simple rules be identified to account for the complex organization and activity of cognitive systems; and second, can that be done without appealing to some sort of central controller to guide the organization and activity? The HKB model of coordination mentioned above is an early success in this approach (Haken et al., 1985). Based on very simple rules, the HKB model could account for the full range of bimanual coordination, including phase transitions among qualitatively different states. Kelso, a contributor to that work, has since expanded the HKB model and developed an investigative framework centered on coordination dynamics. Kelso et al. have been able to build on the simple HKB model of bimanual coordination to successfully model and explain a range of phenomena, from language—e.g., the physiology of sound production (Kelso, Tuller, Vatikiotis-Bateson, & Fowler, 1984) and speech categorization patterns (Tuller et al., 1994)—to phase transitions among coupled neurons (Kelso, Dumas, & Tognoli, 2013). In addition to coordination dynamics, research on self-organization in cognitive systems has continued in the form of complexity matching (Fine, Likens, Amazeen, & Amazeen, 2015; Marmelat & Delignières, 2012) and synergies (Müller et al., 2018).

The fourth, and final concept, is *universality*. As Batterman states, “In its broadest sense, ‘universality’ is a technical term for something quite ordinary” (Batterman, 2019, p. 26). What is “ordinary” is the fact that in nature there are patterns of activity and organization that recur both in different substrates and in various contexts. To put it simply: nature seems to reuse many of the same kinds of structures. Batterman points out the example of rainbows as a universal kind of organization: despite different conditions (e.g., planetary location, temperature, number and size of drops, etc.), rainbows exhibit the same basic pattern. Originating in statistical mechanics, universality—or “universality classes”—refers

to particular kinds of behaviors of systems that are determined by few characteristics, occur across multiple spatial and temporal scales, and are substrate neutral (Batterman, 2000; Thouless, 1989). Universality classes are sets of mathematical models that have the same critical exponents (Wilson, 1983). This means that as the energy of various systems fluctuate, they will approach a fixed point (or critical point) and undergo a phase transition in the same manner independent of the microscopic details of those systems. In other words, the numerical values of the critical exponents that describe the states of various systems as they approach a phase transition are identical across a large group of phenomena that seem to have diverse physical constitutions (Stanley, 1999). Put in terms of dynamical systems: universality refers to the idea that there are large classes of systems that exhibit features mostly independently of the dynamical details of that system (Edelman, 2018). The exemplary case of universality in physics is critical phenomena. Put plainly, systems exhibit critical states when they are poised at the point of a phase transition. Examples of such critical points are exhibited by H₂O undergoing phase transitions among liquid, gas, and solid states. Using verbiage discussed in regard to synergetics, the system-level state of the molecules is an order parameter that holds relationships with various control parameters, such as pressure and temperature. What makes criticality universal is that the relationship among the spatial and/or temporal parts of a system—its correlation length—are the same across systems comprised of various kinds of fluids are the same and exhibit phase transitions at the same point (Batterman, 2019). For example, as water heats up, the H₂O molecules begin to organize into groups of various sizes, such that there are larger groups with smaller groups, and those have smaller groups, and so on. The relationship, or correlation length, among those groupings of H₂O molecules will begin to exhibit a scale-free relationship. As discussed above in relation to NDST, scale-free structures are statistically self-similar patterns or structures at various spatial and temporal scales; and the more scale-free a system is, the more fractal it becomes.

A very appropriate question can be raised at this point: What does universality have to do with cognitive systems? It is becoming evident that as more detailed data is obtained about cognitive systems—from finer spatial and temporal recordings of small-scale neuroanatomy to larger-scale social coordination—the more it appears that they exhibit universal features (Figure 8). Many natural systems exhibit fractal branching patterns and ratios, for example, coral and neurons (Figure 8a,b). It is even the case that nonliving and living systems can exhibit the same universal dynamics. Sandpiles and neuronal networks, for example, can exhibit the same correlation length among their sand-based and neuron-based avalanches (Figure 8c,d). One universality class that is gaining traction in the life sciences is self-organized criticality (SOC; Bak, Tang, & Wiesenfeld, 1988; Favela et al., 2016; Jensen, 1998; Plenz & Niebur, 2014; Pruessner, 2012). SOC refers to the behaviors of a system at different spatial and temporal scales that tend to organize and exhibit phase transitions near critical states. SOC systems have interactions between components across scales that yield coherent global patterns of organization. Because these interactions are in constant flux and occur across scales, the dynamics of SOC systems occupy a wider range of temporal and spatial scales than is typical of comparable systems. As a result, research suggests that SOC is widespread in cognitive systems, from neuronal dynamics (e.g., Beggs & Plenz, 2003) to temporal estimation (e.g., Holden et al., 2009). So, in response to the question posed at the start of this paragraph: If cognitive science is to explain and understand the nature of cognitive systems, it ought to at least take into consideration the role of universal organization and dynamics in those systems. Accordingly, universality can serve to inform hypotheses, guide analyses, and inform explanations.

Note that the role of universality in CSCS is not limited to the statistical mechanics sense of the term. There are other senses in which cognitive systems as complex systems exhibit “universal” features, a number of which have been mentioned above, such as fractals. Catastrophe flags can be understood as another form of universality. For example, hysteresis can be exhibited by a range of phenomena, from magnetization to decision-making. Coordination dynamics offer another form of universality via its application of the HKB model to explain phenomena from finger wagging to neuronal coupling. Utilizing universality as a central guide to discovery (cf. Chemero, 2013) in CSCS is not a radical idea. It is already practiced in many of cognitive science’s subdisciplines, from experimental psychology to neuroscience. Universality is the last of the four key features of cognitive systems understood as complex systems; the others being emergence, nonlinearity, and self-organization. In the next section, I provide an outline for putting those concepts, methods, and theories to work.

5.2 | Doing cognitive science as complexity science

The aim of this section is to synthesize the above material into a coherent investigative framework for cognitive science based on complexity science. The investigative framework on offer is inspired by approaches presented by Cannon (1967) and Thelen and Smith (2006). Thus, without further ado, one way to do CSCS is to follow these steps:

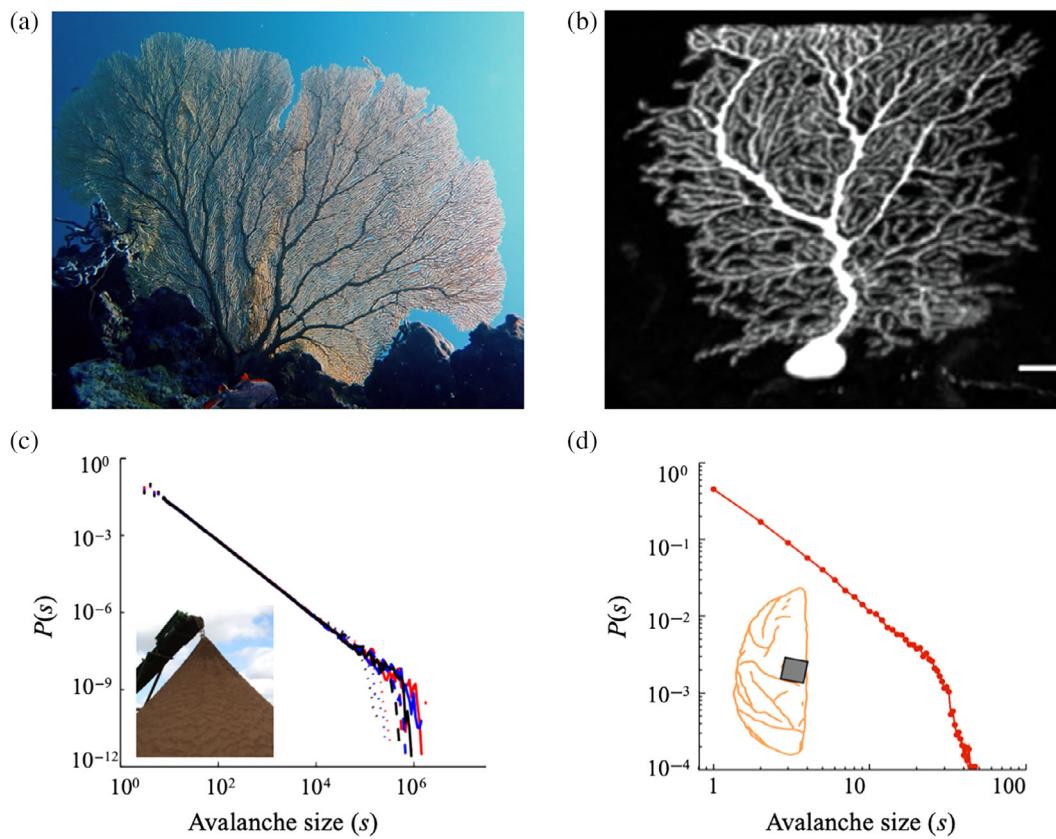


FIGURE 8 Universal spatial structures and temporal dynamics in nature. Coral, like the *Annella mollis*, giant sea fan, are organized in fractal branching structures (a). Cells, such as Purkinje neurons, are organized in fractal branching structures (b). Avalanches can follow power-law distributions in nonbiological systems such as sandpiles (c). Avalanches can follow power-law distributions in biological systems such as neuronal networks in the primary motor cortex. (Modified from Ducarme (2018). CC BY-SA 4.0 (a), Reprinted with permission from Kaneko et al. (2011). Copyright 2011 Public Library of Science; CC BY 4.0 (b), Reprinted with permission from Zachariou, Expert, Takayasu, and Christensen (2015). Copyright 2015 Public Library of Science; CC BY 4.0 and Modified from Craven (2010). CC BY 2.0 (c), and Reprinted with permission from Klaus, Yu, and Plenz (2011). Copyright 2011 Public Library of Science; CC BY 4.0 (d))

1. Identify the phenomenon of interest.
2. Define the order parameter.
3. Define mathematical model to capture the physical model.
4. Solve mathematical model to identify system states.
5. Identify and define control parameters.
6. Measure-the-simulation.

The first step is to *identify the phenomenon of interest*, or target system. Even at this earliest stage of the process, it is justifiable to be theoretically driven. Research questions and topics can be driven by “guides to discovery,” which are sources of new hypotheses for experimental testing (Chemero, 2013). Examples of guides to discovery include affordances in ecological psychology (Chemero, 2013), dynamical similitude, the idea that very different systems can exhibit the same behavior and be governed by the same equations (Amazeen, 2018), and, especially, universality, such as SOC or catastrophe flags.

The second step is to *define the order parameter*. An order parameter is the collective variable that describes the macroscopic phenomenon under investigation (Haken, 1988, 2016). They capture qualitatively different behaviors and organizational structures. Here, “macroscopic” is not objective, but is relative to the research questions. Accordingly, a single neuron can be macroscopic to a microscopic synapse, but then a single neuron can be microscopic to a macroscopic neuronal ensemble. The relative nature of identifying a phenomenon as macro- and microscopic is particularly well-suited to the application of universality classes in research, as they can be scale-free and demonstrated by smaller scales such as neuronal activity and larger scales such as limb movements. At this stage, the order parameter is defined based on early stages of data collection and processing, such as single-neuron recording and motion-tracking of limbs

during a perception-action task. That data is typically plotted (e.g., time-series) in order to generate a physical model that sufficiently matches the actual target system. Such plots can provide a general sense of the nature of the system, which then constrains the definition of the order parameter.

The third step is to *define a mathematical model to capture the physical model*. Although differential equations are typically the go-to for modeling nonlinear dynamic systems, due to the fact that the behavior of such systems can be especially challenging to grasp, difference equations can be suitable (Richardson, Dale, & Marsh, 2014). Whereas differential equations model the continuous evolution of a system, difference equations model system behavior at discrete time steps. Relatively gross models exhibiting discrete data points can help a researcher focus in upon, for example, which catastrophe flag or universality class a system seems to be demonstrating. Eventually, however, investigations of complex systems benefit from the ability to model their behavior as continuous. Doing so can provide finer details that reveal whether a phase transition is really precipitated by hysteresis or if it truly maintains criticality at its attractor states. With that said, because complex systems, with their numerous components nonlinearly interacting at various scales, can quickly become overwhelming for an investigator to model, methodologies from the data sciences are increasingly being applied. One goal of NDST is to identify the governing equations for a system. For reasons just mentioned regarding the staggering complexity of some target systems, data science methods are increasingly being applied to extract governing equations from large data sets. Dale and Bhat (2018) recently imported a novel data science methodology to the investigation of complex cognitive systems: the method of sparse identification of nonlinear dynamics (SINDy; Brunton et al., 2016). Methods such as SINDy can be indispensable at this step in the investigative process. SINDy, for example, provides a way to infer differential equations directly from data, thereby facilitating the ability to define mathematical models that capture the physical model. By the end of this step, the model ought to describe the behavior and dynamic trajectory of the order parameter identified in step one.

The fourth step is to *solve the mathematical model to identify system states*. Once the model is developed in the previous step, it is essential that it be solved so as to verify that it accurately captures the target system. Currently, methods like SINDy have not been applied to highly complex cognitive systems, such as those involving social dynamics. However, as Dale and Bhat (2018) demonstrated, there is proof of concept for the method as it can be successfully applied to well-studied dynamic systems, such as bistable attractor model of human choice behavior, logistic map, and the Lorenz system. With that said, it is at this step in the investigative process that the qualitative features of the framework become essential. As discussed with the model of pendulum dynamics, even in simple cases such as those it can be challenging to solve the equations analytically. For that reason, it becomes necessary to plot the equation in order to assess the model's ability to capture the transition points of the order parameter. Phase space plots (Figure 4 bottom), time-series (Figure 5), and recurrence plots (Figure 7) can be especially useful in this regard.

The fifth step is to *identify and define control parameters*. As a reminder, control parameters are variables that guide the system's dynamics. Due to the slaving relationship with the order parameter and circular causality, control parameters do not cause the order parameter's behavior. For that reason, nonlinear methods are needed to assess the relationships among variables. NDST has accurately identified control parameters for a range of phenomena, such as decision-making (van Rooij et al., 2013), Hénon map (Levi, Schanz, Kornienko, & Kornienko, 1999), perceptual judgments (Frank, Profeta, & Harrison, 2015), and Rayleigh–Bernard convection (Newell, Passot, & Lega, 1993). Correctly identifying control parameters allows researchers to practice other scientific explanatory virtues as control, intervention/manipulation, prediction, and augmentation.

The sixth step is to *measure-the-simulation*. As is clear by now, modeling is indispensable to CSCS, at least in part due to the large amount of data often involved in complex systems research. Modeling virtues such as prediction and simplicity must be balanced with the actual behavior and organization of the target of investigation. Spivey (2018) points out the danger of making the inference from having a model that seems to accurately simulate a cognitive phenomenon to that model revealing the actual ontological structure of that phenomenon. In response, Spivey proposes what I take to be the final step in the doing CSCS: “Measure-the-Simulation.” At its most basic, to measure-the-simulation is to examine the simulations proposed by the models for ways in which the simulation itself might distort or transform the empirical data it is based on. Revealing such distortions or transformations is crucial if researchers doing CSCS want to be confident that their models are true to the systems being investigated.

5.3 | CSCS and “real” cognition

It is crucial that a particular critique of CSCS be addressed. This is a critique that is faced by nearly every investigative framework that claims to be an alternative to TCS. The critique tends to go something like this, “Of course

TABLE 1 Examples of complexity science-based research on phenomena typically considered to be “real cognition” in traditional cognitive science

Real cognition	Complexity science-based research
Cognitive tasks involving emotion, gambling, language, mathematics, N-back, relational, and social	Shine et al. (2019)
Decision-making	van Rooij et al. (2013)
Intelligence	Mustafa et al. (2012)
Learning	Sandu et al. (2014)
Linguistics	Hawkins (2004)
Memory retrieval	Maylor, Chater, and Brown (2001)
Mental representations involving speeded judgment, accuracy of discrimination, and production	Gilden (2001)
Music perception	Pease, Mahmoodi, and West (2018)
Pedagogy	Mason (2008)
Speech	Ramirez-Aristizabal, Médé, and Kello (2018)
Psychopathologies	Brookes et al. (2015)

frameworks such as ecological psychology, enactivism, radical embodied cognitive science, and the like do respectable scientific work and tell us a lot about visual perception, living organisms, and dynamics, respectively; but they do not tell us much at all about *real cognition*. Here, “real cognition” refers to a line of thought in the history of “Western” philosophy and science that treats mind as radically distinct from bodies and action (Ohlsson, 2007). Such is the view of cognition in TCS as essentially a computational and representational process of some sort that is centralized in brains (e.g., Adams & Aizawa, 2008; Chomsky, 2009; Fodor, 2009; Pylyshyn, 1984; Thagard, 2005; Von Eckardt, 1995; cf. Sanches de Oliveira, Raja, & Chemero, 2019). Those processes are purported to underlie mental faculties such as decision-making, language, reasoning, recollecting, mental imagery, etc.; namely, TCS’s phenomena of interest.

Given what has been said thus far about CSCS, I am sympathetic to that critique. I have focused on CSCS’s predecessors, situating it against contrary commitments, and spent much time outlining the concepts, theories, and methods of its investigative framework. Implicit in the discussion has been an agnosticism about what “real” cognition is. Truth be told, I am not sure what cognition is. Moreover, I do not think TCS even knows (Favela & Martin, 2017). But that does not matter for my response to the critique. In the following table, I present 11 categories of phenomena that are usually treated as examples of “real cognition” (Table 1): cognitive tasks involving gambling, decision-making, intelligence, learning, linguistics, memory, mental representations, music perception, pedagogy, speech, and psychopathologies. Alongside each of those is an example of research that applied the concepts, methods, and/or theories of complexity science to investigate and explain them. Although complexity science-based approaches in cognitive science tend to be utilized by nonstandard frameworks, such as distributed, dynamical, ecological, embodied, etc., the examples in Table 1 make evident that CSCS can fruitfully investigate even “real” forms of cognition.

6 | CONCLUSION

CSCS has been presented as an interdisciplinary framework for the investigation of cognition. Within this approach, cognition is treated as complex systems phenomena that exhibit the following four key features: emergence, non-linearity, self-organization, and universality. In order to fruitfully conduct research on systems with those properties, CSCS employs a range of concepts, methods, and theories that are integrated from systems theory, NDST, and synergetics.

CSCS improves upon traditional cognitive science in a number of ways: First, it provides a common set of concepts and methods that can be applied to cognitive phenomena across spatial and temporal scales. Second, as the investigation of cognition becomes a big data enterprise, it benefits from the successful track record complexity science has with making complex phenomena empirically tractable and comprehensible. Third, in addition to having the ability to profitably investigate more traditional forms of cognition, CSCS allows the cognitive sciences to expand their purview to include a wider range of cognitive phenomena, such as distributed, embodied, and extended forms. With all that said, CSCS is unlikely to be the final word on scientific investigations of cognition. Even so, it is worth a shot.

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CONFLICT OF INTEREST

The author has declared no conflicts of interest for this article.

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