Advanced Review

Dynamics of cognition

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The application of dynamical systems methods and concepts to cognitive phenomena has broadened the range of testable hypotheses and theoretical narratives available to cognitive scientists. Most research in cognitive dynamics tests the degree to which observed cognitive performance is consistent with one or another core phenomena associated with complex dynamical systems, such as tests for phase transitions, coupling among processes, or scaling laws. Early applications of dynamical systems theory to perceptual-motor performance and developmental psychology paved the way for more recent applications of dynamical systems analyses, models, and theoretical concepts in areas such as learning, memory, speech perception, decision making, problem solving, and reading, among others. Reviews of the empirical results of both foundational and contemporary cognitive dynamics are provided. © 2012 John Wiley & Sons, Ltd.

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INTRODUCTION

A dynamical system is simply one that changes over time (see Box 1). It is apparent that many of the processes cognitive scientists study—development, learning, the spread of activation in a semantic network, changing patterns of cortical activity, motor behavior, and so on—are intrinsically dynamical. Dynamical systems theory supplies new tools and concepts for understanding these and other cognitive phenomena. The theory offers a full complement of analytical methods (e.g., nonlinear time series analyses) and modeling strategies (e.g., differential equations). Most importantly, it motivates novel theoretical and empirical questions: One may explore the relative stability of a cognitive activity, test for meta- or multi-stability, or test for empirical patterns consistent with scaling behavior, emergence, and self-organization.

These kinds of questions complement those posed by mainstream cognitive science—which traditionally has emphasized static properties of mind such as symbolic representations or structural mechanisms of information processing—by focusing explicitly on change[1–9] (see, e.g., Elman[10] for a dynamical interpretation of connectionist models). Much work in cognitive dynamics was inspired by parallel efforts to understand the dynamics of perception-action.[11–15] Early and significant progress emerged in the domain of motor coordination, where the behavioral phenomena were more obviously dynamical and high-resolution measurement technologies were more readily available.[16] The dynamical account of interlimb rhythmic coordination[12,14] is an example of an early success.

Research in cognitive dynamics is often allied with some version of embodiment.[17–21] Dynamical systems were sometimes framed as replacements for computational-representational accounts,[8,19] as distinct but complementary,[22] or even as consistent with information processing given the implicit computations performed by dynamical systems.[23–25] Whether and how dynamical systems accounts might be reconciled with traditional accounts, they provide a fresh perspective on many foundational problems in cognitive science,[1] including perception-action,[12,14,26] memory,[27,28] word recognition,[29–32] decision making,[33–35] learning,[36–38] problem solving,[39] and language.[10,40]

Progress in applying models, analyses, and the theoretical concepts of dynamical systems to cognition is accelerating and these approaches are now broadly represented in cognitive science. Naturally, the discipline entertains debates about the merits of the perspective.[8,41–46] Rather than rehash those debates, this article seeks to synthesize and summarize recent

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BOX 1

DYNAMICAL SYSTEMS

Dynamical systems are systems whose *state* evolves over time according to a rule. These rules are often written as differential or difference equations. The evolution of the state is a *trajectory* in *state space*, whose coordinates are the variables that fully characterize the system. Trajectories are drawn toward *attractors*, subsets of phase space that are stable solutions to the system equation(s). *Repellers* are unstable solutions, and trajectories are driven away from them. A *bifurcation* is a change in the number or type of solutions, for example the appearance (or disappearance) of an attractor, as some parameter is varied.

Oscillators are one class of dynamical system. Dynamical models of oscillators vary in complexity, from simple, idealized, linear, harmonic motion to more realistic, nonlinear, *limit-cycles*—stable oscillations that result from a balance of energy lost (e.g, to friction) and energy injected into the system. Two variables comprise the state space for a limit cycle—the position and velocity of the oscillating body. A limit-cycle attractor is an elliptical orbit in this two-dimensional space (see Figure 1); if the initial position and velocity are not on the attractor, the system will evolve toward it, or if a perturbation temporarily bumps the system from the attractor, it will quickly 'relax' back onto it. These properties reflect the stability of limit cycles, and contrast with the behavior of *chaotic* dynamical systems, which exhibit different long-term behaviors when initial conditions change and diverge exponentially over time from the previous trajectory when perturbed.

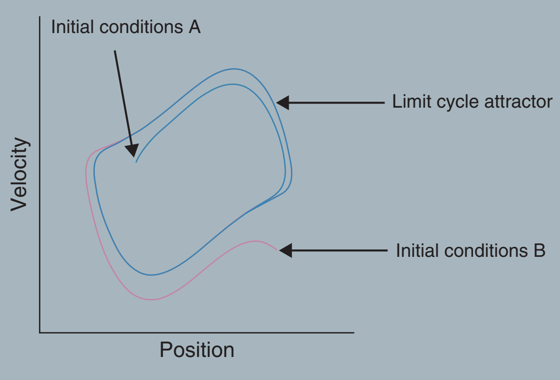

FIGURE 1 | Depiction of a limit-cycle attractor which forms a closed orbit in the velocity-position plane. Two trajectories are shown to converge on the attractor. Each trajectory begins at different initial conditions (A and B) which respectively begin within or outside of the attractor but quickly converge on it. A particular type of nonlinear, limit-cycle oscillator termed van der Pol oscillator is shown. The figure was created with the Matlab tool Limit Cycle Plotter created by Joel Feenstra and available on the Mathworks File Exchange (http://www.mathworks.com/matlabcentral/fileexchange/10191-limit-cycle-plotter).

progress and current themes in dynamical cognitive science.

EARLY INNOVATIONS IN COGNITIVE DYNAMICS

Dynamical concepts are implicit in William James' 'stream of consciousness'[47] and the Gestalt psychologists co-opted field theory from physics.[48] Cybernetics, general systems theory, and catastrophe theory all share conceptual similarities with contemporary dynamical systems theory and they influenced the development of cognitive science. None of those frameworks, however, fully exemplifies the tools and concepts of contemporary dynamical systems and complexity theories (see Box 2). The more contemporary formalization of the concept of self-organization, in particular, represents a major conceptual foundation for contemporary dynamical accounts of cognitive performance.[49] Three key research domains—perception-action, cognitive development, and speech perception—exemplify but do not exhaust early and innovative applications of dynamics and self-organization in cognitive science.

Dynamics of Perception-Action

Perception-action research provided an initial entry point for the application of modern dynamical systems concepts to cognitive science. Stability, emergence, and self-organization featured prominently in dynamic pattern-formation[12] and ecological[57] theories of perception-action. A broad range of modeling and analysis tools motivated by dynamical systems was applied to an equally broad array of behaviors. Coupled nonlinear oscillators were successfully used to model the dynamics of both unimanual and bimanual rhythmic coordination.[59] Haken et al.'s model of bimanual rhythmic coordination[60] not only accounts for initial observations of two spontaneously stable coordination patterns and transitions from one pattern to another as movement frequency increased[61] but also predicts many subtle and unexpected steady-state coordination phenomena that were

BOX 2

COMPLEXITY AND SELF-ORGANIZATION

Complexity and *self-organization* are closely allied with dynamical systems. Complexity is not just 'complicated'. Usually, the term refers to systems comprised of many nonlinearly interacting components that, as a consequence of those internal interactions along with interactions with the environment in which they are embedded, exhibit distinctly recognizable organization at different scales of observation. Self-organization refers to the fact that complex systems subject to appropriate constraints can exhibit spontaneous patterning or order. Classic examples include Rayleigh–Bénard convection[50] and slime molds.[51] The contrast with self-organization is 'other-organization', in which some special component of the system or some agent external to the system is endowed with the ability to organize or command the other components.[52,53]

Self-organizing, complex systems have emergent properties—at macroscopic scales they possesses properties that cannot be reduced to linear interactions among the micro-scale components. Dale et al.[22] pointed out that while emergentism is often dismissed in cognitive science as wishful thinking, emergence is well founded in many other disciplines and its implications for cognitive science ought to be taken seriously in their own right. Self-organization and emergent properties present possible solutions to the problem of how behavior can be regular without there being a regulator[54,55]—these concepts present a principled way to explain cognitive performance without *loans of intelligence*[56] that amount to some form of the homunculus problem.[57,58]

later confirmed in experiments.[62] $1/f$ scaling and fractality were observed in a range of human activity. Standard tools used to asses the structure of variability were applied to perceptual-motor behaviors such as finger tapping,[63–66] eye movements,[67] and locomotion.[68–71] Warren[72] developed a general modeling framework for behavioral dynamics, articulated in terms of the emergence of behavioral trajectories from informational and forceful (mechanical) animal-environment and perception-action couplings in the context of behavioral goals (modeled as attractors) and obstacles (modeled as repellers). The literature on dynamical systems in perception-action is vast, and reviews of this body of research can be found elsewhere.[12,14,73,74]

Developmental Dynamics: The A-Not-B Error

The utility of the dynamical framework in motor behavior and other fields inspired the application of dynamics to human development.[7,75] That work was primarily focused on testing predictions motivated by stability, nonlinearity, emergence, and self-organization.[5] Development, from this embodied, dynamical perspective, is a progression of growth-driven, emergent (not reducible to linear combinations of the components) phenomena in which processes intrinsic to the organism continuously adapt and reconfigure as the organism interacts with its environment. Stage-like, qualitative developmental changes are depicted in this view as resulting from context-sensitive nonlinearities that arise from those interactions.

A workhorse experimental phenomenon for this perspective is the historic 'A-not-B error' described by Piaget.[76] An A-not-B error occurs when an 8- to 10-month-old infant exhibits perseverative reaching toward one location where a toy has previously been hidden (location A) when the toy is newly hidden—while the infant watches—in a new location (location B). Crucially, a time lag is imposed between when the toy is hidden and when the infant is allowed to reach (without the lag, the error does not occur). A dynamic field theory[77,78] model provided a comprehensive account of this phenomenon and also predicted several novel findings.[21,79–82]

The model entails competition between response options in terms of competing activation levels corresponding to a tendency to reach toward one or the other spatial location (A or B) as function of experience and context. When an experimenter draws the infant's attention, and hides the toy in one location (A), the activation level for that location increases temporarily but then begins to decay over time. However, if an activation threshold level is surpassed, the model produces a reach, which also reinforces and increases the activation level associated with the reached location. The repeated accumulation of activation across identical A trials yields a higher overall activation level for the A location than for the B location—even when the toy is subsequently hidden in the B location. The modest increase in activation for the B location when the toy is hidden there in the crucial test-trial decays during the lag period between when the toy is hidden and a reach response is permitted, and thus B's activation is overwhelmed by A activation. An A-not-B error results. The model accurately accounts for both the error phenomenon and the disappearance of the A-not-B error when the child is allowed to reach immediately after the experimenter hides the toy (i.e., no time lag is imposed).

The significance of this model is that it accounts for the A-not-B error by taking into account only the dynamic, embodied behavior of the infant in a particular context. It does not require recourse to explicit representations or static concepts such as object permanency. In fact, the latter issue is important because perseverative reaching can be elicited without presentation of an object of any sort.[79] Dynamic field theory models have additionally been applied to a range of other cognitive and perceptual-motor phenomena, as described in Spencer et al.[81]

Dynamics of Speech Perception

The perceptual-dynamics approach to speech perception illustrates another successful application of dynamical principles to problems in cognitive science beyond motor control.[83,84] Tuller[85] provided an excellent and detailed description of this and related work. This approach borrowed from Kelso's[12] dynamic theory of pattern formation, and focuses on identifying attractors that permit stable patterns of behavior and transitions between stable behavioral modes (behavioral *phase transitions* that map to *bifurcations* in the underlying dynamics) that occur as a *control parameter* is systematically manipulated. In this case, the behavioral patterns relate to the categorical perception of speech sounds (i.e., a subject heard either one word or another) and a control parameter corresponds to the duration of a gap between the sound of the letter 's' and the sound 'ay'. People understand the sound as 'say' for short gap durations and 'stay' for longer gaps. However, the gap duration that distinguishes the phase transition between the two perceptual categories depends on whether the gap is being progressively increased or decreased across successive presentations. Such history dependence is known as *hysteresis*, and it indicates that for certain values of the control parameter the perception is bistable—both 'say' and 'stay' percepts are possible. Such a situation must be modeled as a system with two mutually exclusive perceptual attractors. For some values of the control parameter, both attractors are present. But at some value of the control parameter, participants report only hearing either one or the other word, so the perceptual attractor corresponding to the word that is no longer perceived must undergo a bifurcation, transforming into a repeller, while the attractor for the perceived word remains. The aforementioned phenomena were captured by a differential equation model of categorical speech perception. The model also predicted novel phenomena that were subsequently confirmed experimentally. The Tuller et al. model[84] additionally included ways to account for a number of contextual effects in speech perception and was later elaborated to account for learning effects. The demonstration that speech perception exhibits many of the hallmark properties of nonlinear complex systems, such as phase transitions, bistability, and hysteresis, provided an important benchmark in the development of dynamical systems narratives for cognitive science.

A Summary of the Early Dynamical Systems Framework

These and many other early studies in cognitive dynamics had an important impact on the continued development of theory and empirical research. One emerging viewpoint from this perspective, captured in part by the approach outlined by van Gelder[8], cast the task of dynamical cognitive science as the development of abstract dynamical systems models of cognitive processes. These models would capture the time-evolution of relatively macroscopic state variables that mapped on to some relevant feature of cognitive performance. The scope of dynamical cognitive science has expanded since van Gelder's version of the dynamical hypothesis was formulated, however, and the emphases of the approach have shifted somewhat. Early narratives regarding the soft-assembly of perceptual motor-coordination[57] were later extended with the hypothesis of *soft-assembly of cognitive performance*.[42,86,87] Many new findings appeared in the literature, and new methods were adopted. The following section overviews some of the more recent developments in dynamical cognitive science.

CONTEMPORARY COGNITIVE DYNAMICS

Our review of recent dynamically motivated research in cognitive science is not exhaustive. It necessarily must omit progress in a number of significant areas. These include investigations of (a) movements that embody the cognitive coordination required for successful interpersonal communication,[88,89] (b) decision-making in team sports,[33,90] and (c) insight during problem-solving tasks.[39,91–93] Despite the significance of (a)–(c), a more relevant focus for present purposes is research that addresses the generic issue of whether certain empirical signatures of cognitive dynamics are reliably identifiable in cognitive performance. Those signatures reveal that cognitive and neural processes embody the dynamics of complex, nonlinear systems.

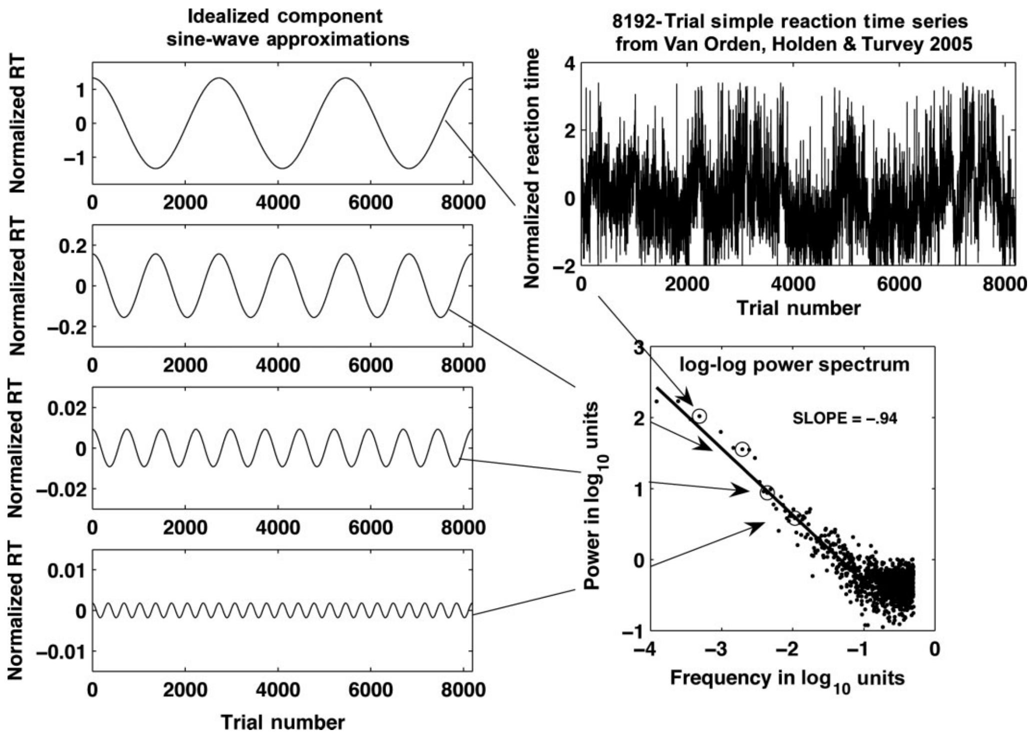

FIGURE 2 | The upper-right plot depicts a trial series consisting of 8192 simple reaction times, produced by a single subject, across a single 3-h experimental session. The *x*-axis tracks the successive trials in the experiment, from the first to the last. The *y*-axis tracks the reaction time in standardized *z*-score units. Directly below the reaction time series is a plot of its power spectral density, or the power spectrum, on double-logarithmic axes. The *y*-axis of the spectral plot corresponds to how big the changes are and the *x*-axis is their frequency of occurrence, on log–log scales. Since $f^{-\alpha} = 1/f^{\alpha}$, the size of change, S(f), is proportional to the frequency, f, of change, as $S(f) \propto 1/f$. The scaling exponent, α, relates the amplitude and frequency of variation and is depicted as $\alpha = 0.94$. It derives from the spectral slope in the lower-right plot. The scaling exponent is an invariant ratio of size and frequency. The plots on the left make explicit what each point in the spectral plot captures. The upper plot is a very low-frequency sine wave and corresponds to the one of the three lowest frequencies that was used to approximate the signal. The specific point it represents is surrounded by a circle, and indicated by the arrow. The remaining plots depict the same information, for progressively higher frequencies of oscillation. The successive axes of the sine plots were dramatically enlarged to make the oscillations visible. (Reprinted with permission from Ref 94. Copyright 2010 Taylor & Francis Ltd)

Scaling Laws in Cognition

The nervous system is a continuously fluctuating excitable medium. Nervous system dynamics unfold within the time interval between the presentation of a stimulus and the collection of a response in a standard laboratory-based cognitive task. How does one understand these cognitive dynamics via behavioral measurements? Cognitive scientists have identified a variety of paradigms to make dynamics available for measurement. One entry point into the dynamics of cognition is a trial series of response times (RTs)—sequences of RTs aligned in the temporal order in which the measurements were taken. There are many statistical analyses that can be applied to a trial series to determine if successive measurements bear any relation to each other, and if so, to assess the nature of that relationship. Figure 2 outlines the basic logic of one such procedure. It is called a power-spectral density analysis (or just spectral analysis for short).

Fractal 1/f Scaling

A fractal is a nested, statistically self-similar pattern. The pattern can be defined over space or time; the concern in cognitive science is typically with patterns of variation in cognitive performance over time. The patterns can be quantified with spectral analysis. Fractals are revealed when the frequency of the oscillations and their respective amplitudes are related by an inverse power-law scaling relation—a linear relation on double-logarithmic scales. The fractal pattern in Figure 2 is called 'pink' or 1/*f* noise. The pattern of variability in the observations that is expressed across short runs of several observations is echoed, statistically, across scores of observations, which are in turn echoed across hundreds, and even thousands of observations. Thus, pink noise represents a nested, statistically self-similar (correlated) pattern of fluctuation across widely ranging runs of successive measurements. A scaling exponent describes the relative coherence of the fractal pattern of correlation entailed in the series of measurements. Assuming appropriate statistical procedures were followed during the analysis, exponents near 1 signal a robust pattern of fractal scaling termed pink noise, exponents that are statistically equal to zero indicate the absence of fractal structure (i.e., randomness—no pattern) in the trial series.

Scaling relations were revealed in a wide range of cognitive performances and physiological measurements as described in previous reviews.[66,94–96] Pink noise was reported in many standard cognitive tasks that measure RTs, such as simple reaction time, word naming, lexical decision, and other decision-based cognitive tasks.[95–98] Similarly, judgment tasks such as temporal and spatial estimation tasks yield 1/*f* scaling.[66,98,99] Explicit daily judgments of self-esteem and implicit measures of racial bias also yield 1/*f* scaling.[65,100] Repetitive speech activity also yields pink noise in a large variety of the possible measures of speech that can be taken.[101] Spectral analysis revealed that these data exhibited an unlikely but orderly dynamic relationship across the various timescales of fluctuation entailed in the signals.

As the early reports of 1/*f* scaling in cognitive performance began to accumulate, a concern was expressed that scientists could be mistaking short-range patterns of autocorrelation for 1/*f* scaling.[98,102,103] The bulk of that initial skepticism was answered, however.[44,104] The empirical patterns held up to rigorous statistical scrutiny, and fractal scaling, in one form or another, has emerged as the most representative and most likely description of the empirical reports.[105,106]

The patterns of 1/*f* scaling expressed in physical systems are typically relatively stable over time. By contrast, the strength and nature of the scaling relations that emerge across human activities tend to vary widely. Tasks that entail significant uncertainly from trial to trial—due either to variations in cognitive load[97] or variability in the sequencing of the within-trial events, such as random inter-trial or inter-stimulus intervals—yield less robust but nevertheless reliable patterns of 1/*f* scaling. In contrast, repeatedly estimating the same temporal duration and RT tasks that use constant inter-trial intervals tend to yield robust and stable patterns of 1/*f* scaling. Differences in laboratory methodology explained some apparent discrepancies in the relative strength of the 1/*f* scaling that was observed in ostensibly identical tasks conducted in different laboratories.[93,107–109]

Given a relatively stable task context, changes from less robust to more robust 1/*f* scaling are associated with motor learning.[110] Similarly, eye-movements while reading become more fluid and display more robust 1/*f* scaling the second time the same passage is read, as contrasted with the same measures taken during a first pass through the text.[111] Dyslexic children display weaker patterns of 1/*f* scaling in their trial-series of word pronunciation times than age-matched, non-dyslexic controls. The dyslexic children's performance is more random and less fluid than their non-dyslexic counterparts.[32] Dual-task (motor + cognitive) performance can also affect 1/*f* scaling. Kiefer et al.[71] had participants walk on a treadmill or perform repeated temporal estimations, or perform both tasks concurrently. When performed separately, each task yielded clear 1/*f* scaling, but in the dual-task condition the variations in cognitive performance became essentially random (although the mean and amount of variability of the temporal estimates did not change compared to the single-task condition). Gait variability was unaffected by the concurrent cognitive task.

There are several competing explanations for 1/*f* scaling in cognition, but the only one that has gained any traction in predicting new phenomena is the straightforward hypothesis equating 1/*f* noise with evidence of coordinative activity across many temporal scales.[30,106,108,112,113] Fractal patterns of variability in repeated measurements, such as 1/*f* scaling, constitute the empirical pattern that is symptomatic of the coupling that gives rise to coordination. Self-organizing physical, chemical, and biological systems exhibit 1/*f* scaling in their patterns of temporal evolution. This is consistent with the proposition that cognitive performance unfolds as a quasi-coordinated whole, a perspective that challenges the time-honored search for isolable components of mind. Moreover, when one considers that multiple measures of the same behavior can yield statistically independent 'streams' of 1/*f* scaling,[101] the alternative hypothesis that each measurement of 1/*f* scaling derives from a corresponding component structure entails an absurd, never-ending proliferation of *ad-hoc* modules.[42]

Once scaling is identified in a system a natural working hypothesis is that the system may express additional forms of scaling. In fact, many additional scaling relations were identified in human performance. Several predate the identification of 1/*f* scaling by a century or more, while others were only recently described. Perhaps the first scaling relation identified in human performance is now called Stevens' law, and refers to the fact that to achieve algebraic changes in perceived stimulus magnitude human sensory systems (vision, audition, tactile sense, etc.) require objective changes in stimulation that follow a power law. The observed pattern highlights one key implication of scaling behavior. It is well known that a variety of anatomical and nervous system processes support any given sensory system, but functionally, the system appears to behave as a coordinated whole. The pieces of the system reveal little about the system's holistic behavior.

Another historic scaling relation, often called Zipf's law, refers to the fact that for most large samples of written text the relationship between the frequency of use of any given word is a power-law function of the relative usage rank-order of the word. The pattern is apparently expressed universally across many individual texts, corpora of aggregate text, and across both modern and ancient languages. Zipf's original hypothesis was that the scaling relation is a result of two general competing constraints on communication: Speakers emphasize easy-to-recall, frequent words, whereas listeners prefer distinctive, unambiguous, low-frequency items. Zipf saw the power law as a natural product of this competition.[114,115]

Scaling in RT Distributions

Distributions of RTs provide another entry point into scaling laws in cognition. Inverse power-law distributions entail a prominent skew, such that the probability of observing a particular event (a RT, for instance) is the inverse of the RT value raised to a scaling exponent α, i.e., $p(RT) \approx RT^{-\alpha}$. An inverse power-law distribution entails a more dramatic positive skew than an exponential distribution, for example. An inverse power-law tail implies circular (feedback) coupling among processes that govern the system. Thus, power-law distributions are also associated with complex systems that coordinate their behavior across multiple temporal or spatial scales.

Dynamic systems accounts of cognitive activity rooted in the principle of circular causality predict the presence of power-law distributions of measures of cognitive performance.[30] Recently, inverse power-law distributions were identified with the positive skew that is ubiquitous in the slow tails of RT distributions arising from laboratory-based cognitive tasks such as word recognition and decision-making. Statistical analyses of several extant large-scale RT databases demonstrated robust evidence for power-law behavior in the slow, stretched tails of RT distributions.[116,117] The fact that inverse power-law scaling is intrinsic to both the time course of cognitive acts and the temporal patterns of correlation in RTs implicates a key role for dynamics in contemporary theoretical narratives of cognitive activity.

Scaling in Memory 'Foraging'

Another power law hypothesis, put forward by Rhodes and Turvey,[28] was inspired by animal foraging behavior. Remarkably, foraging behavior is generally well described in the terms of the far-from-equilibrium dynamics of contemporary thermodynamics.[118,119] This source of hypotheses in thermodynamics is certainly credible given the fact that all living things are thermodynamic engines. Neuroimaging studies reflect that fact in their reliance on the BOLD signal of metabolism and glucose uptake, for example—the metabolic processes of the 'thermodynamic' brain.[120,121]

The foraging model predicted a Lévy distribution of temporal and spatial intervals of activity, which yields another power law. Animal memory is associated with foraging, and Rhodes and Turvey[28] proposed that human symbolic memory could, in a sense, behave as an internalization and elaboration of foraging. They tested this idea by looking at the distribution of inter-recall-intervals in a free recall task. Participants recalled as many animals as possible in a 20-min time interval and the duration of the intervals between successive, recalled animal names was recorded. The resulting distribution of recall intervals followed a power-law with an exponent of $\alpha = 2$, the predicted Lévy distribution.

Scaling relations are surprisingly common in human activities. They are associated not only with motor performance, where they were first identified, but also with perceptual, linguistic, and other cognitive performances—activities that in some sense are thought to set humans apart from other organisms. But the fact that scaling relations are observed in these activities seems to contradict the distinction and enhance the status of human activity as akin to the behavior of other natural systems. Rhodes and Turvey,[28] for example, interpreted their findings as suggesting that memory is strongly influenced by external (environmental) structure, in much the same way as actual animal foraging is influenced by the distribution of food sources and geographical features in the environment. This interpretation is consistent with the claims of stronger versions of embodiment that cognition is not limited to the mind alone. Distributed cognitive systems are the result of informational couplings within and across agents, and between agents and their environments.[52] In this approach, rather than processing and computation the new emphasis is on coordination and organization.[86]

Continuous Dynamics of Mental Processes

Another implication of a dynamical systems approach to cognition is that cognitive processes flow over time, evolving from one state to another continuously and smoothly. This contrasts with the assumption that cognition involves discrete computational steps tantamount to discontinuous jumps in mental states. Spivey and colleagues[122,123] outlined one broad approach to conceptualizing cognition as a continuous, dynamical process. In this perspective, cognitive processes are understood as trajectories that evolve continuously in a very high-dimensional, neural state space. Attractors located in different regions of this space correspond to different mental states. Changes in mental state amount to the trajectory departing one basin of attraction (a region in which trajectories will be drawn to a certain attractor) and being drawn to a different attractor location.

This perspective was bolstered by studies that employed dense-sampling methodologies to identify continuous, graded effects of cognition on the dynamics of response trajectories;[16,124] a detailed description of one implementation of this methodology is described elsewhere.[125] One dense-sampling methodology requires participants to move a mouse pointer from a start location to click on a response item.[126,127] A similar method takes advantage of motion-capture or similar technologies (e.g., a Nintendo Wii or Microsoft Kinect) and allows participants to use arm movements to point toward a response item.[36,128] Studies using these and related methodologies have provided evidence that cognitive processing unfolds over time during the production of the response. For example, Spivey et al.[127] had participants move the mouse toward one of two pictures that corresponded to the object of a spoken phrase such as ‘click the candle’. If the two response options were a picture of a candle and a picture of a piece of candy, the ambiguity arising from the shared initial phonemes between ‘candle’ and ‘candy’ was reflected in a reliable curvature of the mouse trajectory that was absent when the distractor item was unambiguous (see Figure 3). Syntactical ambiguity similarly generates curvature in mouse trajectories when participants had to click on a picture that was described by a phrase.[129] Mouse trajectories also exhibit graded curvature toward alternate response items when participants must choose a response to

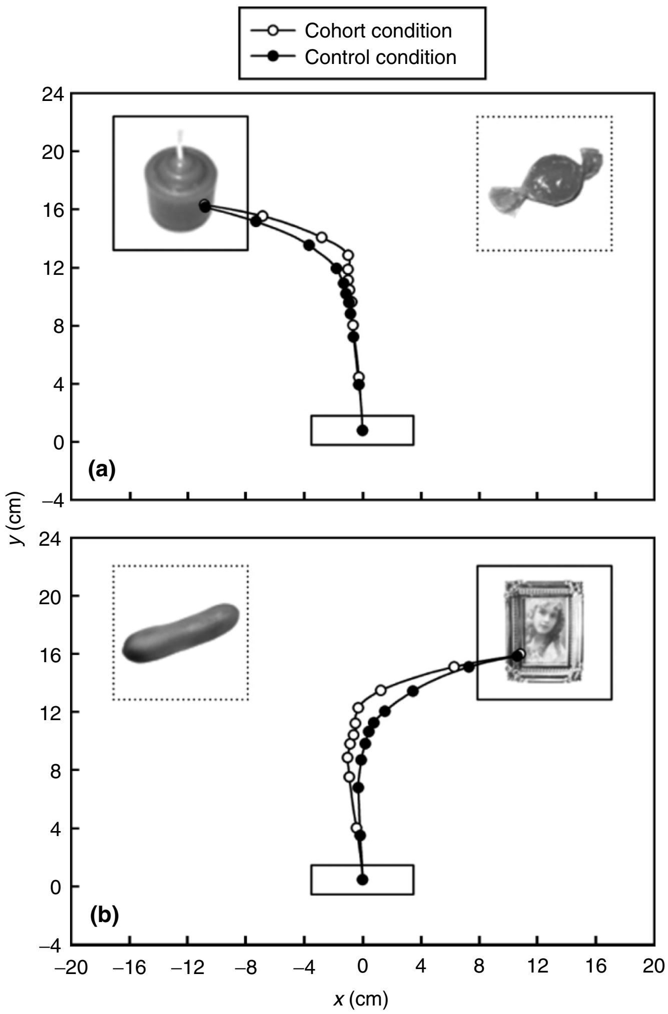

FIGURE 3 | Example of a curved response trajectory that reveals a continuous change in cognitive dynamics. The task is to move the mouse pointer from a start box to click, in the case of the top panel, on the candle. When a picture of a candle and a piece of candy are presented (Cohort condition), the mouse trajectory shows a systematic bias in the direction of the competing response item (the candy), but this bias is not seen in a control condition when the response alternative is not phonologically similar to ‘candle’. (Reprinted with permission from Ref 127. Copyright 2005 National Academy of Sciences, U.S.A.)

items that vary along a continuum of truth values (e.g., 'Should you brush your teeth everyday?' vs. 'Is murder sometimes justifiable?' vs. 'Is a thousand more than a billion?').[35] Continuous response trajectories' amount and structure of variability also embody the uncertainty and increased certainty that respectively characterize early and later stages of learning in a paired-associate memory task,[36] deception,[130] and a variety of factors related to social cognition.[131–134]

The results of these and other dense-sampling studies initiated fruitful exchanges about the implications of this work for cognitive science and, in particular, for dynamical interpretations of cognitive processes.[16,124] Apparently, cognitive processing does not necessarily arise in singular, discrete, punctate (or nearly so) steps, but rather it unfolds continuously over time. The time scales in question here are very rapid compared to the time scale of a motor behavior or of a social interaction, for example, but, nevertheless, cognition is apparently no less dynamical than other behaviors with long-recognized dynamics. Moreover, the transparency of the cognitive processing in the response trajectory calls into question the assumption of independent, serially arranged, cognitive and motor modules,[16] an implication that is broadly consistent with many takes on embodiment. Cognition 'leaks' into action; motor responses reveal the underlying perception, decision making, categorization, and other types of cognitive processes as they are occurring simultaneously with the early stages of producing the response. A related, novel hypothesis, inspired by the work by Spivey and colleagues on the continuity of mental processes,[122,123] is that cognition may not just 'leak' into response trajectories, but the motor dynamics of response trajectories might likewise influence cognition. For example, decisions could be biased toward a certain response option if the motor system is perturbed toward it during the execution of the response.

These new ways of thinking about the relations between cognition and action may have implications for understanding dual-task performance involving concurrent cognitive and motor activities. Often, such forms of dual-tasking are associated with a performance decrement, and typically the decrement is attributed to some sort of information processing limitation such as structural interference or limited attentional capacity.[135–138] Dynamical systems inspires alternative conceptions of dual-task performance as a higher-order, synergistic coordination that spans the two tasks and in the process induces reparameterization[139] of motor performance.[71,140–143] For certain tasks, this perspective yields precise, quantitative predictions about the effects of cognitive performance on the noisiness and stability of motor performance. These alternative conceptions are motivated further by a number of apparent violations of the dictum that dual-tasking results in degraded performance—for example findings that postural stability is improved when a standing person engages in a concurrent mental task.[144–149]

CONCLUSION

This article reviewed cognitive dynamics. In broad strokes, cognition expresses the properties one expects from complex, perhaps nonlinear dynamical systems. It would be naïve, however, to make a conclusive and restrictive claim that cognitive performance is effectively, exclusively, and simply dynamical. Ongoing research enterprises continually point in new directions and alternative descriptions of cognitive activities inspire specific new hypotheses and new ways of modeling and understanding cognition.

Despite the promise reviewed here, challenges do remain for the cognitive dynamics framework. Some tasks are easily adapted to continuous, dynamic measurement, while other widely trusted paradigms are not. Training in nonlinear methods and statistics is increasingly available through summer workshops and online resources,[150] but it is still rare in cognitive science or psychology graduate programs. Additional development and validation is needed for methods that enable large-scale efforts to mine multi-modal data sets and to capture cognition in real-world behavioral contexts.

A contrast of the cognitive dynamics framework and conventional cognitive theory underscores the degree to which available research and statistical methods constrain theory in cognitive science.[94,108] Methods and statistics, be they linear or nonlinear, implicitly codify their assumptions in the studied phenomenon—but novel tools continually reveal novel patterns in performance. For instance, Ihlen and Vereijken[106] report evidence that the $1/f$ scaling in trial-series of RTs may be more accurately described as a form of multifractal scaling—a more complex pattern, wherein the scaling relation, itself, fluctuates across time. Clearly, an increased openness to alternative characterizations of both familiar and novel cognitive phenomena will benefit cognitive science in the long run.

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