

The Emergent Coordination of Cognitive Function

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1/f scaling has been observed throughout human physiology and behavior, but its origins and meaning remain a matter of debate. Some argue that it is a byproduct of ongoing processes in the brain or body and therefore of limited relevance to psychological theory. Others argue that *1/f* scaling reflects a fundamental aspect of all physiological and cognitive functions, namely, that they emerge in the balance of independent versus interdependent component activities. In 4 experiments, series of key-press responses were used to test between these 2 alternative explanations. The critical design feature was to take 2 measures of each key-press response: reaction time and key-contact duration. These measures resulted in 2 parallel series of intrinsic fluctuations for each series of key-press responses. Intrinsic fluctuations exhibited *1/f* scaling in both reaction times and key-contact durations, yet the 2 measures were uncorrelated with each other and separately perturbable. These and other findings indicate that *1/f* scaling is too pervasive to be idiosyncratic and of limited relevance. It is instead argued that *1/f* scaling reflects the coordinative, metastable basis of cognitive function.

Keywords: *1/f* noise and scaling, criticality, metastability, relative coordination, emergent cognitive function

Almost daily, new reports appear of brain areas for mental faculties. Apparently any kind of thing that a person can do—recognize familiar proper nouns (Addis, McIntosh, Moscovitch, Crawley, & McAndrews, 2004), analyze the positions of pieces on a chess board (Atherton, Zhuang, Bart, Hu, & He, 2003), respond to unfair economic proposals (Sanfey, Rilling, Aronson, Nystrom, & Cohen, 2003), puzzle over moral dilemmas (Greene, Somerville, Nystrom, Darley, & Cohen, 2001), appreciate jokes (Moran, Wig, Adams, Janata, & Kelley, 2004), ejaculate (Holstege et al., 2003), whatever—lives in a different spot or spots in the central nervous system. Skeptical scientists find this troubling (Uttal, 2001), including skeptics who practice neuroimaging (e.g., Fuster, 2003). At conferences one too often hears the old joke about the drunk looking for lost keys under the lamppost because the light is better there. The joke and similar sentiments apologize for the widespread use of subtractive and correlational methods in neuroimaging. These dissociative and associative methods too easily (inevitably) parse brain activity or behavior into hypothetical faculties (Van Orden, Pennington, & Stone, 2001). The methods have

well-known logical shortcomings that make it difficult to justify isolation or localization of function, regardless of whether the data are brain images or behavior (Bub, 2000; Shallice, 1988; Uttal, 2001).

But shortcomings aside, suppose one accepts the patterns of activation inferred from neuroimaging data as reflective of locations where neural resources are more or less engaged by cognitive performances. Even then, cognitive functions are difficult to localize because cognitive performances appear in neuroimages as numerous patches of activation distributed across the brain (Basar, 2004; Friston, Phillips, Chawla, & Buchel, 2000; Maestu et al., 2003). In fact, as a general rule, activation has been found to become more widespread as task difficulty increases (Carpenter, Just, Keller, Eddy, & Thulborn, 1999; Jonides et al., 1997; Petersen, van Mier, Fiez, & Raichle, 1998). Evidence for widespread activation naturally leads one to ask whether it might reflect widespread networks of neural processing (Damasio & Damasio, 1994; Posner & Rothbart, 1994). This question has been pursued with neuroimaging methods that attempt to measure the “functional connectivity” of brain regions (Horwitz, 2003; Patel, Bowman, & Rilling, 2006; Sun, Miller, & D’Esposito, 2005), and complementary anatomical methods have been made more accessible by recent technological advances (Norris, 2006; Symms, Jager, Schmierer, & Yousry, 2004).

It should come as no surprise that evidence for functional networks has been easy to find. After all, it is generally accepted that different areas of the brain must coordinate themselves to support cognition and behavior (see Bressler, 2002; Bressler & Kelso, 2001), and electrophysiological evidence for coordination has been available for some time now (Freeman, 1975; Mayville, Bressler, Fuchs, & Kelso, 1999; Wallenstein, Kelso, & Bressler,

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1995). One can even look to behavior itself for more transparent evidence of coordination. Consider how walking, for instance, requires a clear and strong functional connectivity among the limbs and their anatomical components (given that connectivity corresponds to dependencies among component activities). This connectivity can be measured directly in the regular relations among degrees of freedom in movements, and coordination in simple model tasks has been studied rigorously for decades (Bernstein, 1967; Turvey, 1990; von Holst, 1939/1973). It is only common sense that coordinations in motor activity should have corresponding coordinations in neural activity, and this common sense has been verified in the laboratory (Kelso, 1995; Lagarde, Tognoli, & Kelso, 2006; Mayville, Jantzen, Fuchs, Steinberg, & Kelso, 2002).

What does the coordination of brain and body tell us? Consider that not only walking but virtually all behavioral and cognitive performances are fundamentally phenomena of coordination, for what kind of performance is the product of one component working in isolation? To wit, locomotion requires the coordination of perceptual and motor systems (e.g., Loomis, Dasilva, Fujita, & Fukusima, 1992; Warren, 2006), and the notion that social interactions are like dances is more than a fanciful metaphor (Schmidt, Christianson, Carello, & Baron, 1994; Shockley, Santana, & Fowler, 2003). Even more strictly cerebral performances like solving a puzzle can be viewed as coordinations of mental activity, although the components to be coordinated are less obvious in these cases. In this regard it is interesting to note that the growing paradigm of embodied cognition is based on the idea that bodily functions, which are transparent phenomena of coordination, are internalized to support more abstract cognitive functions (Gibbs, 2006; Lakoff & Johnson, 1980; Varela, Thompson, & Rosch, 1991). Thus embodied cognition may entail a fundamental commitment to coordination.

The coordinative basis of cognition is problematic for functional localization because, in its fullest sense, coordination entails emergence (Kugler, Kelso, & Turvey, 1980, 1982). It means that components interact so completely that one can no longer parse their individual contributions in the collective activity of the whole. Each component may contribute its own potentials and constraints in shaping this collective activity, but the activity of each component is strongly interdependent with the activities of potentially many other components (Bressler & Kelso, 2001). For instance, the eyes and hands and visual cortex and motor cortex are all functionally distinct, but these distinctions are blurred in measures of activity by strong mutual dependencies among components. There are also mutual dependencies between an organism's components and its environment that create an organism-environment system (Gibson, 1979). The consequence of such pervasive dependencies is that isolated physiological activity cannot be used to isolate component functions because activities and functions are always realized in the context of the coordinated whole.

Thus the coordination of brain and body may entail an emergent basis of behavioral and cognitive function (Pattee, 1976). This general and admittedly sweeping statement raises questions about its testability and meaningfulness. Is it too vague to be tested? Is there actually a face of emergent coordination that can be recognized and observed throughout human behavior and its physiological underpinnings? Can experiments be designed to test whether

this face truly reflects a general principle of coordination, as opposed to some quirk or byproduct of processes that are mostly irrelevant to behavioral and cognitive function?

We propose that the emergent basis of behavioral and cognitive functions can indeed be tested, and this is the primary aim of the current study. Our reasoning begins with an overwhelming and ubiquitous empirical fact. Across dozens of observations of neural and behavioral phenomena, and literally thousands of observations across the sciences, researchers have found that different kinds of physical, chemical, biological, psychological, and social systems all exhibit the same kind of fluctuation whose statistical character has proven to be as puzzling as the fluctuation is ubiquitous. The fluctuations of all of these kinds of systems have been found to follow a lawful scaling relation known as *1/f noise*, which is also known as the more aptly named *1/f scaling*.

The statistical character of *1/f scaling* and its connection with emergent coordination is explained in the next section, but suffice it to say here that the origins of *1/f* fluctuations in nature remain a matter of debate despite decades of research and thousands of studies (a bibliography can be found at <http://www.nslj-genetics.org/wli/1fnoise>). Some researchers have argued that *1/f* fluctuations reflect a general and essential principle of emergent pattern formation in complex systems (Bak, 1996; Bassingthwaite, Liebovitch, & West, 1994; Camazine et al., 2003; Gisiger, 2001; West & Deering, 1995), including cognitive systems (Gilden, 2001; Kelso, 1995; Van Orden, Holden, & Turvey, 2003).

Others find it hard to believe that so many different kinds of systems, with such different components, would all have a common basis of operation. The alternative is to believe that each system has some idiosyncratic source of *1/f* fluctuations (e.g., see Baillie & King, 1996; Ivanov, Amaral, Goldberger, & Stanley, 1998; Pressing, 1999; Wagenmakers, Farrell, & Ratcliff, 2004, 2005). In psychological science, two idiosyncratic hypotheses represent the majority of these alternative explanations. The first is that, whatever the myriad sources of fluctuation are that impinge on psychological measurements, they happen to combine into a *1/f* scaling relation. The second is that some ongoing process like vigilance, cognitive control, or mental set happens to generate *1/f* fluctuations. These hypotheses differ from emergent coordination in that they restrict the purview of *1/f* scaling and thereby diminish its general relevance to cognitive science.

In the present study we aimed to provide more discriminating evidence than heretofore available on the origins of *1/f* scaling in cognitive performances. In four experiments, we used simple and choice response tasks to test the generality of *1/f* scaling in human behavior. The results show that *1/f* scaling is too general to fit within the restricted purviews of idiosyncratic accounts, whereas emergent coordination accommodates the results naturally. Thus the pervasiveness of *1/f* scaling in cognitive performance is evidence that cognitive functions are generally, perhaps universally, formed as emergent patterns of physiological and behavioral activity.

Emergent Coordination and *1/f* Scaling

The connection between emergent coordination and *1/f* scaling has its roots in von Holst's (1939/1973) classic studies of coordination in a wide range of biological organisms. These studies

identified two modes of activity among anatomical components. These modes are complementary and arise in general when components have preferred patterns of activity that are diversified across the system in question. To illustrate, two of von Holst's primary biological models were the lipfish and the centipede. In the lipfish the components are fins, the activities are oscillations of the fins, and each fin has a preferred frequency of oscillation. The centipede is similar except the components are oscillating legs.

In one mode, each component may be found to produce its preferred oscillatory pattern of activity regardless of the other components. Von Holst (1939/1973) referred to this tendency towards independence of components as the *maintenance tendency*. The opposing mode is characterized by a tendency for components to produce in unison a single, common pattern of activity. Von Holst referred to this tendency as the *magnet effect*. Importantly, neither extreme creates the coordination used for lipfish swimming or centipede walking. Instead, locomotion is accomplished by a balance of these opposing tendencies that gives rise to what von Holst referred to as *relative coordination*. The components work together to create a globally coherent pattern of activity, yet each component maintains its potential for independence.

The balance of relative coordination allows components to flexibly reorganize themselves into a variety of stable patterns of activity. Von Holst (1939/1973) demonstrated this flexibility in the centipede by removing some number of its legs and observing how the remaining legs maintained functionality (Van Den Berg, 2000). He found that locomotion was transformed to the insect gait when three pairs of legs were left and the quadrupedal gait when two pairs of legs were left. These alternate modes of locomotion do not appear to be hard-coded motor programs in the centipede's nervous system that come on-line when a certain number of legs are lost. They instead appear to be a generic potential of the structural and dynamical relations among its physiological and anatomical components. Removing legs alters system constraints, causing the relative coordination of components to reorganize and thereby reimplement the function of locomotion in their new context.

Von Holst's (1939/1973) hypothesis of relative coordination has since been vigorously extended and elaborated to explain a wide variety of human movement patterns (Kelso & Clark, 1982; Schmidt, Beek, Treffner, & Turvey, 1991; Schwartz, Amazeen, & Turvey, 1995; Turvey, 1990), and more recently patterns of human neural activity as well (Bressler & Kelso, 2001; Friston, 1997; Le Van Quyen, 2003; Linkenkaer-Hansen, Nikouline, Palva, & Ilmoniemi, 2001). In these later works, relative coordination is replaced with the concept of *metastability* that originates from principles of thermodynamics. Metastability generalizes the balance between independence and interdependence beyond oscillators to non-linear components of all kinds. It formalizes this balance in terms of a complex system near its *critical point* between ordered and disordered phases.

Critical points are well-known phenomena of thermodynamics, and models of criticality have been applied to complex systems throughout nature. We illustrate the defining features of a critical point using a model reported by Usher, Stemmler, and Olami (1995) that demonstrates the connections between metastability, emergent pattern formation, and 1/f scaling. The authors presented their model as a simulation of center-surround receptive fields that are commonplace in research on neural mechanisms of perceptual

processing. Neuronal units in the model had excitatory (center) and inhibitory (surround) inputs that came from neighboring units, as well as external inputs.

Simulations showed that sufficiently weak external inputs did not allow stable patterns of activity to form across the neuronal grid, and thus activities fell into a disordered (fluid) phase. Sufficiently strong external inputs created a fixed pattern of evenly spaced clusters (reflecting the center-surround structure), and thus activities fell into an ordered (crystalline) phase. The transition between phases was not a smooth function of input strength. Instead there was an abrupt transition between phases (i.e., the critical point) in which metastable patterns could form. At the critical point, neuronal neighbor interactions were sufficiently strong to allow patterns to form, but also sufficiently weak to allow patterns to fluctuate intrinsically and change in response to external inputs.

Intrinsic pattern fluctuations had corresponding fluctuations in individual neuronal activities, and Usher et al. (1995) showed that these fluctuations followed a 1/f scaling relation. 1/f fluctuations are statistically special in many respects (see Wagenmakers et al., 2004), but here we just point out that they are scale-invariant: A time series plot of 1/f fluctuations has the same "look and feel" as one zooms in or out to see more fine-grained or coarse-grained features of the fluctuations. The 1/f scaling relation is typically expressed in the frequency domain, however, rather than the time domain. A time series can be transformed into the frequency domain by Fourier analysis which represents the series as a set of sine waves, each with an associated frequency and power. For 1/f fluctuations, power and frequency are inversely related (hence the name 1/f scaling). The scaling relation is parameterized by an exponent α ($1/f^\alpha$), where $\alpha = 1$ for ideal 1/f scaling.

The center-surround model is just one example from decades of research showing that complex systems near their critical points universally exhibit scaling laws, including 1/f scaling (for reviews, see Bak, 1996; Solé & Goodwin, 2000; Sornette, 2004). This groundwork is the basis for interpreting evidence of 1/f scaling in behavioral and neural activities as evidence for the metastable basis of cognitive function. Such evidence has been found in measures of mental rotation and translation (Gilden, 1997), visual search (Aks, Zelinsky, & Spratt, 2002), simple classifications (Kelly, Heathcote, Heath, & Longstaff, 2001), lexical decision (Gilden, 1997), word naming (Van Orden, Holden, & Turvey, 2003), and color and shape discrimination (Gilden, 2001).

In these and other examples, 1/f scaling was found in the intrinsic fluctuations of performance. Empirical intrinsic fluctuations are analogous to intrinsic pattern fluctuations in the center-surround model: They both express dynamics that are attributable primarily, if not solely, to the system itself. Such intrinsic dynamics are expressed most clearly in the model when measurements are unperturbed by changes to external inputs. Empirically speaking, constancy is achieved by taking the same measurement repeatedly without changing the experimental or environmental conditions. One of the clearest examples in human behavior was provided by Gilden, Thornton, and Mallon (1995). They asked participants to estimate from memory the same temporal interval (e.g., 1 s) or the same spatial interval (1 in.) over and over again, without feedback. Spectral analyses showed a clear 1/f scaling relation in the intrinsic fluctuations of interval estimates.

In summary, we hypothesize that cognitive functions are expressed as metastable patterns of neural and behavioral activity. These patterns are able to form because interactions among neural and bodily components tend to be near critical points between ordered and disordered phases of activity. The $1/f$ signature of metastable pattern formation is universal to intrinsic pattern dynamics, which are expressed as intrinsic fluctuations of cognitive performances. Intrinsic fluctuations are elicited experimentally in repeated behaviors, which on the surface may seem far removed from the cognitive performances that researchers are typically interested in. However, note that intrinsic fluctuations can, in principle, be elicited from any kind of behavior, including all behaviors that experimentalists use to express cognitive performances. Moreover, repeated behaviors involve the same physiological and anatomical components as more typical cognitive performances. These points strongly suggest that intrinsic fluctuations are not separate from cognitive functions. Instead it appears that intrinsic fluctuations can be elicited from the interactions of any and all system components involved in the emergence of cognitive functions.

Experiments 1 and 2: Multilevel Alternatives to Emergent Coordination

While $1/f$ scaling is relatively new to the psychological sciences, the concept of intrinsic fluctuation is not. Experimentalists have long realized that behavior fluctuates “on its own” over time, no matter what is done to hold conditions constant. However, it is traditionally assumed that such fluctuations are irrelevant to cognition and other psychological processes. The rationale is that behaviors are always subject to many streams of random perturbations (e.g., Klein, 1997). Some perturbations may come from subtle changes in the environment, and others may come from flux within the system itself. In most statistical models, these assumed perturbations are approximated as independent samples of measurement error.

However, there are always physiological and cognitive processes unfolding more slowly than the chosen pace of measurement, regardless of whether repeated measurements are taken once per second or once per hour. Some of these processes may slowly unfold on the scale of ultradian or circadian rhythms, for example (Dijk, Duffy, & Czeisler, 1992). Others may unfold on the faster time scales of hormonal, respiratory, cardiac, vascular, autonomic, and cellular processes. All may impinge on measures of cognitive performance, creating both “random” and slowly changing contributions to measured values (Newell, 1990; Simon, 1973). Such contributions will create trends across measurements, such as runs of relatively high or low values (Bills, 1935).

So, a more complicated *multilevel* account combines all of the above sources of fluctuation in repeated behaviors (Bills, 1943). Although a multilevel account may seem appropriate for intrinsic fluctuations, the problem is that mixtures of independent processes across multiple timescales are unlikely to yield the $1/f$ scaling relation that characterizes intrinsic fluctuations (Hausdorff & Peng, 1996). Such mixtures are more likely to yield a blend of independent and correlated contributions to measurements that deviate from the $1/f$ scaling relation. In fact there has been some debate about whether observations are better explained as such blends rather than true $1/f$ scaling, but the evidence for $1/f$ scaling

is now clear (Farrell, Wagenmakers, & Ratcliff, 2006; Thornton & Gilden, 2005; Van Orden, Holden, & Turvey, 2005; Wagenmakers et al., 2004).

Evidence for $1/f$ scaling has led some researchers to simply stipulate that multilevel processes combine to mimic a $1/f$ scaling relation (e.g., Amaral et al., 2001; Beran, 1994; Granger & Joyeux, 1980; Pressing, 1999; Wagenmakers et al., 2004). A psychological version of this hypothesis is that unconscious, subconscious, and conscious processes combine as a $1/f$ scaling relation in measurements of human behavior (Ward, 2002). Such hypotheses provide no theoretical explanation for why the mixture of timescales should line up in a $1/f$ scaling relation, but they are consistent with the evidence, at least in human performance data.

We designed Experiments 1 and 2 to put multilevel accounts to the test by investigating the generality of $1/f$ scaling in cognitive performance. Previous studies have tested for $1/f$ scaling in only one dependent measure at a time, whereas we examined two parallel measures of key-press responses: *reaction time* and *key-contact duration*, the latter being the brief duration of time that the key makes contact with its sensor for a typical key stroke. The question is whether one or both dependent measures may exhibit $1/f$ scaling in their intrinsic fluctuations, and if both, whether the $1/f$ fluctuations in each measure are correlated with each other.

The most straightforward and natural prediction of multilevel accounts is that reaction times and key-contact durations should exhibit correlated $1/f$ fluctuations. This prediction stems from the assumption that, whatever physiological or cognitive processes impinge on key-presses and key-releases to create $1/f$ fluctuations, they will impinge on both aspects of performance in a correlated manner. This is most intuitive and obvious for processes that unfold over the course of minutes and hours rather than seconds or milliseconds. For instance, suppose that fluctuations in vigilance create slow fluctuations of change across dozens of key-press responses spanning minutes or even tens of minutes of measurement time. All other things being equal, if these fluctuations influence performance at all, then their influence should create correlations in the fluctuations of different measures of performance. Therefore, if vigilance helps to create $1/f$ fluctuations in key-press responses, then it should help to create the same $1/f$ fluctuations in reaction times and key-contact durations.

Emergent coordination, by contrast, leads one to predict distinct $1/f$ fluctuations for distinct measures of system behavior. Consider again the model of criticality reported by Usher et al. (1995). Metastable patterns of activity were not uniform across the neuronal system, and hence $1/f$ fluctuations were not uniform across its neuronal components. Thus even if reaction times and key-contact durations are measures of the same underlying system near its critical point, they should exhibit distinct $1/f$ fluctuations provided that they reflect the activities of distinct sets of system components. For instance, the neural and muscular groups that most directly influence reaction times are different from those that influence key-contact durations. Also, in the present experiments, keys were not pressed so successively close in time or with such force as to impose correlations on the kinematics of key-presses and -releases. Therefore, the intrinsic fluctuations in reaction times were free to vary independently of key-contact durations.

The multilevel and coordinative accounts also make divergent predictions with respect to the introduction of random perturbations to measurements. First of all, both accounts agree that ran-

dom perturbations should interfere with the expression of intrinsic fluctuations, thereby weakening the 1/f scaling relation. However, the multilevel accounts predict that any perturbation should jointly affect both reaction times and key-contact durations. Because the two measures are yoked in real time (key-contact duration begins as reaction time ends), any perturbation to one should affect both in terms of their ability to express the combined 1/f effect of multilevel processes. By contrast, emergent coordination predicts perturbations to selectively affect one or the other dependent measure, provided that their intrinsic fluctuations are free to vary independently of one another.

In Experiment 1, we manipulated the relative presence or absence of perturbations by making the timing of simple response cues either unpredictable or predictable, respectively. In Experiment 2, we manipulated the relative presence or absence of perturbations by making the identity of choice response cues either unpredictable or predictable, respectively. Predictable cues create relatively constant experimental conditions from one trial to the next because each new trial contains no new information. Unpredictable cues create perturbations because conditions change randomly from one trial to the next.

The predictions of each account as outlined above were the same for both experiments. The multilevel accounts predict correlated 1/f fluctuations in reaction times and key-contact durations, and they predict 1/f fluctuations in both measures to be clearest when cues are predictable. By contrast, emergent coordination predicts uncorrelated and independently perturbable 1/f fluctuations in reaction times versus key-contact durations.

Experiment 1 Method

Participants. Eighteen student participants were recruited from George Mason University. Sixteen were undergraduates who participated for course credit, and 2 were graduate students who were compensated for their participation. Eleven were female, 17 were right-handed, and all had normal or corrected vision.

Apparatus. An IBM PC computer running Windows 2000 was used. The experiment-running software used Microsoft DirectX for timing, stimulus presentation, and keyboard input. A 17-in. cathode ray tube monitor running at a 70-Hz refresh rate was used to present stimuli, and a PS/2 keyboard was used to collect responses.

Procedure. Each participant was seated in a quiet experimental room about 2 feet (0.61 m) in front of a computer monitor placed on a table with its keyboard. Participants were instructed to rest their arm on the table and place their index finger on or next to the space bar. For each trial, a large white *X* appeared periodically on the monitor. Participants were instructed to hit the space bar key as soon as they saw each *X* response cue. No mention was made of how long the space bar should be held down. Participants were instructed to wait for each cue to appear before responding and were warned that a loud beep would sound if the space bar was pressed prior to a cue's appearance.

Each cue was displayed for 57 ms in the center of the computer screen, ± 7 ms due to monitor refresh (all stimulus displays included ± 7 -ms variability due to monitor refresh). Immediately following each cue, a pair of dashes was displayed in the center of the monitor and remained visible until the participant pressed the space bar in response. The time before the next cue appeared was

linked to the release of the space bar (participants were not told this, nor was it noticeable). In the fixed-cue condition, cues appeared 1,000 ms from the release of the space bar. In the variable-cue condition, release-cue intervals were sampled from an exponential distribution with a mean of 1,000 ms, a minimum of 1 ms, and a maximum of 12,000 ms. The exponential distribution created a flat hazard function within the lower and upper bounds, which meant that the probability of receiving a cue was constant as a function of wait time from the previous cue (Simpson, Braun, Barga, & Newman, 2000).

Each participant was presented with one experimental block of 1,100 fixed cues and one experimental block of 1,100 variable cues. Each block took about 25 min to complete. The order of blocks was counterbalanced across participants. Each participant was given a short break in between blocks, and each participant was told whether the upcoming block of cues was predictable or unpredictable. A short practice block was given prior to each experimental block. A reaction time and a key-contact duration was recorded for each response to each cue. Reaction time was the time from the appearance of the response cue *X* until the space bar made contact with its sensor. Key-contact duration was the time that passed from contact to release of the space bar. Delays in detection times of contact and release were estimated to be 0–7 ms.

Experiment 1 Results and Discussion

Data preparation. The data were prepared for analyses as follows. First, anticipatory responses and responses with latencies over 1,000 ms were removed. For the remaining responses, a mean and standard deviation were calculated for each series of reaction times, for each participant in each condition. The same was done for each series of key-contact durations. Responses with reaction times or key-contact durations that were outside of three standard deviations from their respective mean were then trimmed. The last 1,024 data points in each trimmed data series were standardized (*Z* scores) and selected for analysis, because some analyses required that the number of data points be equal to a power of 2. To gauge the effects of trimming on spectral portraits of 1/f scaling, we created artificial data series of 1/f scaling and removed data points at random. For percentages of removal on the scale of trimming done herein (no more than 1%), spectral slopes were virtually unaffected.

Data analysis. The goal of our analyses was to measure the extent of 1/f scaling in each data series using techniques that classify noises. There are many such techniques, and each has its strengths and vulnerabilities (Eke, Herman, Kocsis, & Kozak, 2002; Rangarajan & Ding, 2000). We employed three methods of analysis in order to provide convergent support for our statistical conclusions and to best protect those conclusions from the vulnerabilities of any single analysis (Delignières, Torre, & Lemoine, 2005; Holden, 2005). All three of the methods provide an estimated scaling exponent that roughly characterizes the given data set. More exact estimates are difficult to determine (Thornton & Gilden, 2005) but were unnecessary for our purposes because no current theory of 1/f scaling in cognitive performance makes exact predictions about the values of scaling exponents. At best, the current theories may predict the class of noise to be observed (i.e., the range in which exponents should fall) and the direction of

effect that an experimental manipulation will have on the scaling exponent. The methods we used are well-established for these purposes.

Using spectral methods, power densities were estimated using a 126-frequency window-averaging technique as in Van Orden, Holden, and Turvey (2003). Each series was first linearly detrended, and then we estimated its spectral slope by fitting the power spectral density estimates of the lowest 63 frequencies (lowest 50%) with a regression line in log-log coordinates (data were not bandpass filtered but were passed through a triangular window prior to spectral analysis). Ideal $1/f$ scaling gives a slope equal to -1 , whereas ideal white noise gives a slope equal to 0 . Empirical $1/f$ scaling will appear as a slope between -1 and 0 . Power estimates in the upper frequencies were not used because they can be affected by limitations in the measurement protocol. These limitations include error in the measurement device as well as behavioral fluctuations that occur at frequencies higher than those detectable by the protocol, which become aliased. The two other methods that we employed were detrended fluctuation analysis (Peng, Havlin, Stanley, & Goldberger, 1995) and standardized dispersion analysis (Bassingthwaight et al., 1994). These methods are derived from fractal theory and essentially describe how the patterns of variability in the series scale as a function of sample size. Detrended fluctuation analysis is known to be reliable and robust (Eke et al., 2002) and does not require the arbitrary setting of parameters, as does spectral analysis. Dispersion analysis is also highly reliable, but linear and quadratic trends may bias its output. We therefore removed both linear and quadratic trends for dispersion analyses.

The three methods are complementary in that the strengths of each tend to compensate for the weaknesses of the others. For instance, spectral techniques are susceptible to a range of statistical artifacts and require significant preprocessing as a consequence

(see Press, Teukolsky, Vetterling, & Flannery, 1992). Nonetheless they give a clear picture of $1/f$ scaling in the low frequency region of the spectral plot (Van Orden et al., 2005). Dispersion analysis is generally more reliable than spectral analysis, but its outcome may sometimes be biased by simple long-term trends (these trends are not a problem for spectral analysis; Holden, 2005). Detrended fluctuation analysis is a fractal method that can be applied to nonstationary signals. It is not susceptible to most statistical artifacts or to long-term trends, but it can falsely classify certain types of signals as fractal (Rangarajan & Ding, 2000). By using all three methods together, we ensured the reliability of our conclusions. To simplify reporting, we converted the outputs of the dispersion and detrended fluctuation analysis into spectral slopes (Eke et al., 2002).

Time series illustrations. To convey a better sense of the task and resulting behavior, we have illustrated a time series of fixed cues and compared this with a time series of variable cues in Figure 1. Time is to the right along the horizontal axis. Each X represents a cue, and each down-arrow represents the downward press of the response key. Each trailing up-arrow represents the subsequent release of the key. In the upper diagram, the space from each up-arrow to the following X is shown to be constant, representing the fixed release-cue intervals. In the lower diagram, these spaces vary in width, representing the variable release-cue intervals.

Reaction times are marked by the wider brackets, and key-contact durations are marked by the narrower brackets. These widths appear unchanging in the diagrams; the actual fluctuations are plotted in the two time series below each diagram. Reaction times are pulled out and illustrated on the left, and key-contact durations are pulled out to the right. All the time series come from 1 participant's trimmed and normalized data. Data from the same participant's blocks of fixed and variable cue trials (1,024 points

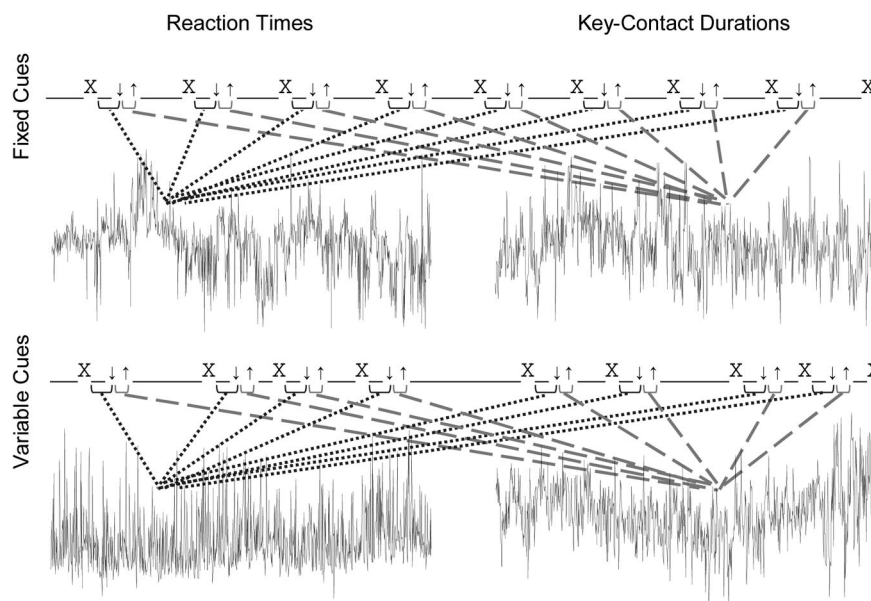


Figure 1. Diagram of 1 participant's data from Experiment 1, shown with timelines that illustrate sequences of fixed (top) and variable (bottom) release-cue intervals. Each X represents a cue; each down-arrow represents the downward press of the response key; and each trailing up-arrow represents the subsequent release of the key.

each) are plotted above and below, respectively, with reaction time (left) or key-contact duration (right) on the y -axis. $1/f$ scaling in trial-to-trial fluctuations can be seen as undulations in the plotted time series that vary in height (amplitude) and width (frequency). Notice the relative lack of large-amplitude, low-frequency undulations in the series of reaction times for the variable cue condition compared with the other three conditions. This visible effect of variable cues shows up as a shallower spectral slope in the power spectrum results that are reported next.

Spectral analyses. In Figure 2, two power spectra are plotted in log-log coordinates, one for reaction times and one for key-contact durations. Each point represents the estimated power at a given frequency, averaged across participants, in responses to fixed or variable cues. A regression line was fit for each type of cue to the averaged log power estimates in the lower half of the log frequency range. The slope of the regression line provides a rough estimate of the $1/f$ scaling exponent. As noted earlier, power estimates in the higher frequencies were avoided because they are muddled by aliasing, measurement error, and other limitations of the experimental protocol. Figure 2 shows a clear change in slope in the spectral density estimates for reaction times to fixed versus variable cues, but no such change for key-contact durations. In Table 1, this effect is shown in the averages of spectral slopes, along with their standard errors and supporting t -test results. Results from all three methods of analysis are shown in terms of spectral slopes for purposes of comparison.

The outcomes of each of the three methods supported the outcome of every other. $1/f$ scaling was apparent in all conditions, as evidenced by the consistently negative slopes and the persistent linearity at the lowest measured frequencies. But more relevant to the research question, the estimated $1/f$ scaling exponent for reaction times was closer to the zero slope of white noise when cues were variable as opposed to fixed. By contrast, the effect of cue predictability on $1/f$ scaling in key-contact durations was substantially less.

Correlations and means. Correlation coefficients were calculated for each participant's time series and then averaged across participants. The mean coefficients for blocks of variable and fixed cues were 0.00 and -0.22 , respectively (this weak negative cor-

relation in the predictable cue condition failed to replicate in any condition of the remaining experiments). Finally, the perturbations introduced by variable cues were accompanied by slower reaction times overall compared with fixed cues: $M = 311$ ms versus 173 ms, respectively, $t(1, 17) > 1,000$. By contrast, there was no a priori reason to expect a difference in mean key-contact durations. In fact there was a small but reliable effect opposite to that for reaction times: key-contact durations for variable versus fixed cues averaged 114 ms versus 130 ms, respectively, $t(1, 17) = 5.2$, $p < .001$.

Summary. Results showed clear evidence of $1/f$ scaling in the fluctuations of reaction times as well as key-contact durations when cues were timed regularly (predictably). The critical finding was that, for a given series of key-press responses, $1/f$ fluctuations in reaction times were not reliably correlated with $1/f$ fluctuations in key-contact durations. Another finding further supported the apparent independence of these two measures: Unpredictable cues caused the estimated $1/f$ scaling exponent to decrease in reaction times but not key-contact durations.

The apparent independence of fluctuations in reaction times and key-contact durations does not fit with the multilevel accounts of $1/f$ fluctuations. The reason is that these accounts lead one to expect reaction times and key-contact durations to provide yoked samples of physiological or cognitive processes that combine coincidentally to produce $1/f$ fluctuations. By contrast, the findings are naturally accommodated by emergent coordination because $1/f$ fluctuations are theorized as a general property of metastability that is evident wherever intrinsic fluctuations are measured, including parallel and uncorrelated measures of intrinsic fluctuation.

In Experiment 2, a perturbation of trial information was used instead of a perturbation of trial timing. Specifically, the timing of cues was always fixed, and predictability was manipulated in terms of the identity of cues in a choice response task. Cues in this case indicated which key to press, right or left. Predictable cues followed a simple alternating pattern that allowed participants to anticipate the identity of the response key on every trial. Unpredictable cues were chosen at random. Thus the conditions and predictions are essentially the same as in Experiment 1.

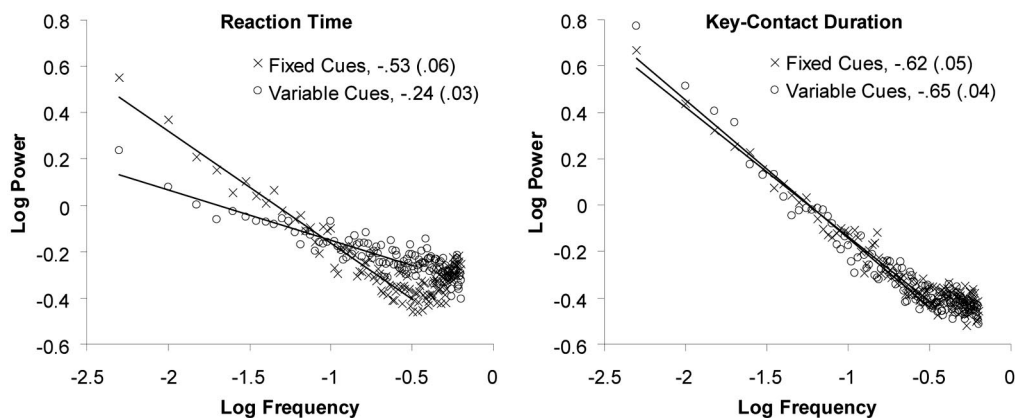


Figure 2. Spectral plots for reaction times (left) and key-contact durations (right) from Experiment 1, each plotted separately for blocks of fixed versus variable release-cue intervals. Average slopes of regression lines are shown with their respective standard errors.

Table 1
Spectral Slope Results for Experiment 1

Measure	Spectral		DFA		Dispersion	
	Fix.	Var.	Fix.	Var.	Fix.	Var.
Reaction times						
<i>M</i>	-0.53	-0.24	-0.44	-0.19	-0.39	-0.19
<i>SE</i>	0.06	0.03	0.06	0.02	0.05	0.02
<i>t</i>		3.78		4.32		4.26
<i>p</i>		.002		<.001		.001
Key-contact durations						
<i>M</i>	-0.62	-0.65	-0.49	-0.57	-0.45	-0.49
<i>SE</i>	0.05	0.04	0.04	0.04	0.03	0.03
<i>t</i>		0.81		2.08		1.50
<i>p</i>		.432		.053		.152

Note. *t* and *p* are paired-samples *t*-test results. Spectral = spectral analysis; DFA = detrended fluctuation analysis; dispersion = dispersion analysis; fix. = fixed release-cue intervals; var. = variable release-cue intervals.

Experiment 2 Method

Participants. Eighteen undergraduate students from George Mason University participated in the experiment for course credit. Twelve were female, 16 were right-handed, and all had normal or corrected vision.

Apparatus and procedure. The apparatus and procedure were the same as in Experiment 1, except for the following differences. The response cue was either < or >, instead of an X. Participants were instructed to press the left-arrow key for the former, and the right-arrow key for the latter, always using the index finger of their dominant hand. In the predictable-cue condition, the cue identity followed a simple, constant pattern that repeated over trials. The pattern was left-left-right-right-left-left-right-right and so on. In the unpredictable-cue condition, right or left cues were chosen at random from trial to trial, with equal probability. Release-cue intervals were fixed at 1,000 ms in both conditions.

Experiment 2 Results and Discussion

The methods of data preparation and analysis were the same as in Experiment 1. A time series of patterned cues is illustrated and compared with a time series of random cues in Figure 3. Results of the spectral analyses are presented in Figure 4 and Table 2. Results were essentially parallel to those of Experiment 1. 1/*f* fluctuations again appeared to be present in all conditions, but spectral slopes for reaction times were reliably more shallow and closer to white noise when cues were random and unpredictable as opposed to patterned and predictable. The effect of cue predictability on spectral slopes for key-contact durations was again marginal at best. Fluctuations in reaction times and key-contact durations were again relatively independent, as evidenced by weak correlation coefficients for blocks of random cues (mean *r* = .13) as well as patterned cues (mean *r* = -.05). Finally, the random cue condition induced slower reaction times (*M* = 478 ms) compared with patterned cues (*M* = 277 ms), *t*(1, 17) > 1,000. There was no such difference in key-contact durations, with means of 126 ms and 124 ms for random and patterned cues, respectively, *t*(1, 17) = 0.57.

The results of Experiment 2 replicated and extended those of Experiment 1. Predictability was manipulated in terms of response choice instead of response timing, yet the pattern of effects remained the same. These findings once again do not fit with multilevel accounts of 1/*f* fluctuations. Multilevel accounts hold that 1/*f* scaling has a singular collective source, but how could reaction times and key-contact durations fail to provide correlated samples from this collective source? Moreover, how could perturbations to reaction times fail to interfere with the expression of this collective source in key-contact durations as well? To illustrate the problem, consider how implausible it is that slow fluctuations in vigilance could have uncorrelated effects on the downward versus upward movement components of key-press responses. To be uncorrelated in this case would mean that some periods of high vigilance, for example, would cause reaction times and key-contact durations to decrease, whereas other periods of high vigilance would have divergent effects on these dependent measures. This makes no apparent sense.

By contrast, emergent coordination leads one to expect the observed pattern of results. Series of key-press responses, like any other behavioral act, should yield intrinsic fluctuations under constant measurement conditions. Intrinsic fluctuations should express the 1/*f* signature of metastability that is hypothesized to be universal to physiological and behavioral activity. As shown in Usher et al.'s (1995) model, all components involved in metastable pattern formation will produce 1/*f* fluctuations and different components may produce distinct, uncorrelated streams of 1/*f* fluctuations. Reaction times and key-contact durations are presumably influenced by different sets of neural and muscular components and hence are expected to produce uncorrelated and separately perturbable 1/*f* fluctuations. This is precisely what was found in Experiments 1 and 2.

Experiments 3 and 4: Two-Source Alternatives to Emergent Coordination

From a reductive point of view, the results of Experiments 1 and 2 would appear to indicate that there are two distinct sources of 1/*f*

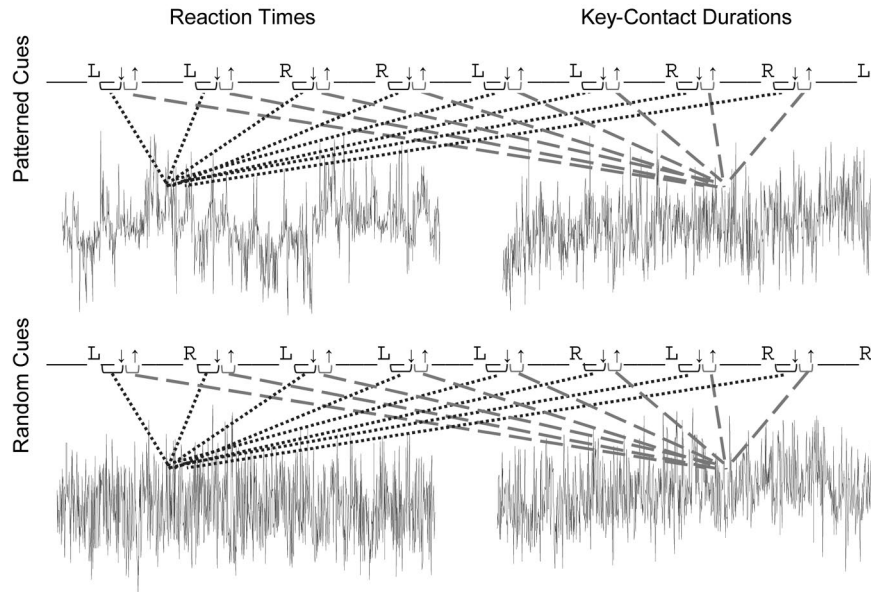


Figure 3. Diagram of 1 participant's data from Experiment 2. Response data from a block of patterned cue sequences are plotted on top, and data from a block of random cue sequences are plotted on the bottom. Each L represents a left-arrow cue, and each R represents a right-arrow cue. Each down-arrow represents the downward press of the response key, and each trailing up-arrow represents the subsequent release of the key.

fluctuations, one that is expressed in reaction times and another that is expressed in key-contact durations. A multilevel account, for example, would therefore have to posit two distinct collections of processes that each combine in a $1/f$ scaling relation. One collection would need to affect reaction times but not key-contact durations, and another collection would need to have the opposite effect. This kind of multilevel account appears highly unlikely, so we abandon it here.

What other kind of idiosyncratic account might explain our results thus far? Before addressing this question, we wish to point out that, to our knowledge, no one has previously proposed separate processes for these two measures. They are being considered now only to cope with the finding of uncorrelated and separately

perturbable $1/f$ fluctuations. Thus the reader might ponder whether an ad hoc, idiosyncratic account can or should be pursued. The answer to "can it be pursued" will always be "yes" because there is no end to ad hoc explanations of scientific phenomena (Einstein & Infeld, 1938/1966; Quine, 1961). The answer to "should it be pursued" depends on whether some plausible ad hoc story might prove its value through reliable and surprising predictions, thereby gaining purchase on explanation (cf. Lakatos, 1970). The problem now is that there is no intuitive reason to assign separate, idiosyncratic sources of $1/f$ scaling to reaction times versus key-contact durations. Emergent coordination may also appear to be ad hoc because it presumes separate components underlying reaction times and key-contact durations. However, the prediction of $1/f$

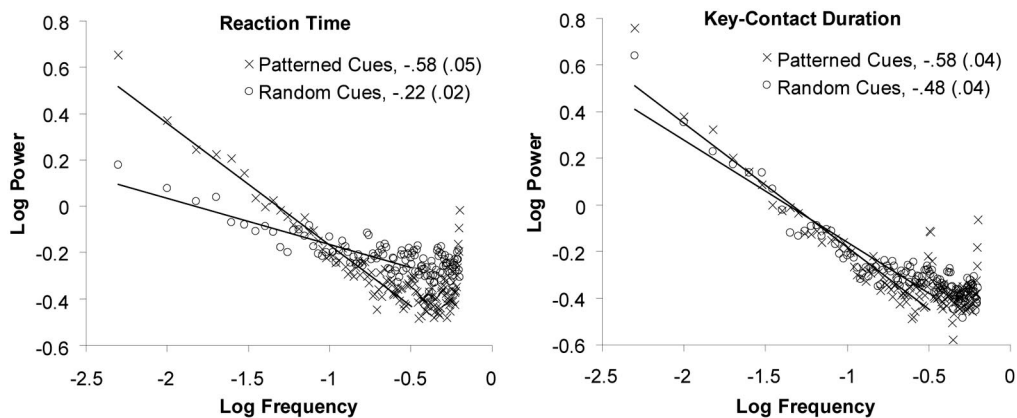


Figure 4. Spectral plots for reaction times (left) and key-contact durations (right) from Experiment 2, each plotted separately for blocks of patterned versus random cue sequences. Average slopes of regression lines are shown with their respective standard errors.

Table 2
Spectral Slope Results for Experiment 2

Measure	Spectral		DFA		Dispersion	
	Patt.	Rand.	Patt.	Rand.	Patt.	Rand.
Reaction times						
<i>M</i>	-0.58	-0.22	-0.53	-0.18	-0.48	-0.15
<i>SE</i>	0.05	0.02	0.04	0.02	0.03	0.03
<i>t</i>		6.85		inf.		inf.
<i>p</i>		<.001		<.001		<.001
Key-contact durations						
<i>M</i>	-0.58	-0.48	-0.51	-0.46	-0.50	-0.41
<i>SE</i>	0.04	0.04	0.03	0.04	0.02	0.04
<i>t</i>		1.97		1.23		2.12
<i>p</i>		.065		.235		.049

Note. *t* and *p* are paired-samples *t*-test results. Spectral = spectral analysis; DFA = detrended fluctuation analysis; dispersion = dispersion analysis; patt. = patterned cues; rand. = random cues; inf. = approached infinity.

fluctuations and the potential for uncorrelated $1/f$ fluctuations are both firmly grounded in theories of metastability and criticality.

By contrast, a two-source account would have to posit two independently motivated sources of $1/f$ fluctuations in reaction times and key-contact durations. Perhaps the most plausible (albeit ad hoc) two-source account is to associate reaction times with controlled strategic or cognitive processes (e.g., decision processes and the like) and key-contact durations with automatic motor processes (e.g., biomechanical processes and the like). Despite its plausibility, this runs into immediate problems. For example, one would have to explain why cognitive processes do not impinge upon key-contact durations, despite previous studies showing that cognitive factors can have their effects throughout the kinematics of response behavior (Abrams & Balota, 1991; Kawamoto, Kello, Jones, & Bame, 1998; Kello, 2004). One also confronts general critiques of explanations that invoke idiosyncratic strategic or controlled processes that cannot be falsified (Besner, 1984; Bradley & Forster, 1987).

The latter problem is the biggest problem. The account so far simply posits one source of $1/f$ scaling in reaction times and another in key-contact durations and gives them some plausible names. For these names to be useful, the account needs to provide some insight into why controlled processes and motor processes would each produce their own patterns of $1/f$ scaling. If the answer is that $1/f$ scaling is a general property of all cognitive and behavioral processes, then one has come upon the hypothesis of emergent coordination. The alternative to emergent coordination in this case is that there is something peculiar about the conditions of intrinsic fluctuation that infuses $1/f$ scaling throughout the behavior being measured.

The most conspicuous peculiarity in research to date on $1/f$ scaling in cognitive performance is that participants are always asked to repeat a given behavior many times. This protocol is justified by the need to measure intrinsic fluctuations as clearly as possible, but it is also justifiable to ask whether there might be something peculiar to long periods of repetition that create $1/f$ fluctuations. For instance, repetition might create a behavioral

situation in which each next act is generated as a function of the previous act with respect to system variables that control the act, including uncorrelated variables. This iterative map could be formalized as a set of *autoregressive* functions, and autoregressive functions can be formulated to generate $1/f$ fluctuations (Beran, 1994; Granger & Joyeux, 1980). Thus the separate $1/f$ fluctuations in reaction times and key-contact durations may reflect separate iterative maps created by repetition.

Experiments 3 and 4 were designed to test the repetition account of $1/f$ fluctuations in cognitive performance. If $1/f$ scaling is the result of producing repeated behaviors, then eliminating repetition should weaken or eliminate $1/f$ scaling. In Experiment 3, predictable and unpredictable conditions were created with an equal lack of repetition in both conditions. Specifically, left and right response cues were chosen at random in both conditions, but cues were made predictable in one condition by previewing them 1,000 ms prior to the elicitation of each response. Previewing allowed each response, left or right, to be anticipated prior to the time of response execution. The repeated behavior account predicts *no* effect of previewing on $1/f$ scaling because responses were not repeated in either condition.

Emergent coordination, by contrast, associates $1/f$ scaling with intrinsic fluctuations, and this association leads to a different prediction. Previewing allows intrinsic fluctuations to manifest clearly in key-press responses for the same reason as in Experiments 1 and 2: The response cue itself provides no new information because the response has already been specified when it appears. Therefore previewing should provide a clearer picture of $1/f$ scaling in reaction times compared with unpreviewed cues. And because the cues have no impact on key-contact durations, they should be unaffected by the previewing manipulation.

Experiment 3 Method

Participants. Eighteen undergraduate students from George Mason University participated in the experiment for course credit.

Ten were female, 16 were right-handed, and all had normal or corrected vision.

Apparatus and procedure. The apparatus and procedure were the same as in Experiment 2, except for the following differences. Cues were chosen at random in both the previewed and unpreviewed conditions. The difference was that previewed cues were presented 1,000 ms prior to a signal to respond. Specifically, a $<$ or $>$ cue was displayed upon release of the key from the previous response. After 1,000 ms, a dash was displayed to either side of the cue. Participants were instructed to respond according to the cue as soon as the dashes appeared (i.e., the signal to respond), but no sooner. The dashes remained on the screen until the participant responded. The unpreviewed cues were presented simultaneously with the signal to respond.

Experiment 3 Results and Discussion

The methods of data preparation and analysis were the same as in Experiments 1 and 2. Results of the spectral analyses, presented in Figure 5 and Table 3, were essentially the same as those of Experiments 1 and 2. $1/f$ scaling again appeared to be present in all conditions, but spectral slopes for reaction time data were reliably shallower when cues were unpreviewed (unpredictable) as opposed to previewed (effectively predictable). By contrast, previewing had no effect on the prevalence of $1/f$ fluctuations in key-contact durations.

Fluctuations in reaction times and key-contact durations were again independent of each other, as evidenced by the weak correlation coefficients for blocks of unpreviewed cues (mean $r = .07$), as well as previewed cues (mean $r = -.08$). Finally, reaction times to unpreviewed cues were slower ($M = 500$ ms) than those to previewed cues ($M = 313$ ms), $t(1, 17) > 1,000$. There was no such difference in key-contact durations, with means of 121 ms and 128 ms for unpreviewed and previewed cues, respectively, $t(1, 17) = 1.52$, $p > .15$. This pattern of means is analogous to that found in Experiments 1 and 2.

The results of Experiment 3 failed to corroborate the repeated behavior account. The prediction was that $1/f$ scaling should be equally weak or absent in both conditions because neither of them

included repetitive patterns of responding; the response direction was always changed randomly from trial to trial. Nonetheless the $1/f$ scaling relation in reaction times was weakened only when cues were unpreviewed, which implicates predictability as the driving factor, analogous to Experiments 1 and 2. Key-contact durations were dissociated from reaction times, which is also analogous to Experiments 1 and 2.

Experiment 4 provided a second test of the repeated behavior account that complements Experiment 3. In a repeated pattern condition, participants were instructed to generate responses from memory in the pattern of left–left–right–right and so on, as in the predictable condition of Experiment 2. In a random choice condition, participants were instructed to generate sequences of left and right responses by their own choice, as if they were simulating an unbiased coin toss on each trial. Thus random choice responses were not repeated in a predictable pattern, yet they were “predictable” to participants in the sense that they did not have to respond to an unpredictable cue.

The repeated behavior account predicts that $1/f$ fluctuations in reaction times should manifest most clearly in the repeated patterned condition but less so or not at all in the random choice condition. By contrast, the association of $1/f$ scaling with intrinsic fluctuations predicts that $1/f$ scaling should be equally prevalent in both conditions because the same behavior is produced for each response cue within each condition and no perturbations are introduced by extrinsic changes from one cue to the next.

Experiment 4 Method

Participants. Eighteen undergraduate students from George Mason University participated in the experiment for course credit. Twelve were female, 16 were right-handed, and all had normal or corrected vision.

Apparatus and procedure. The apparatus and procedures were the same as in Experiment 1, except for the following differences. Release–cue intervals were fixed at 1,000 ms in both the predictable and unpredictable conditions. In the repeated pattern condition, participants were instructed to press the left- and right-arrow keys in the repeating sequence of left–left–right–right. Participants

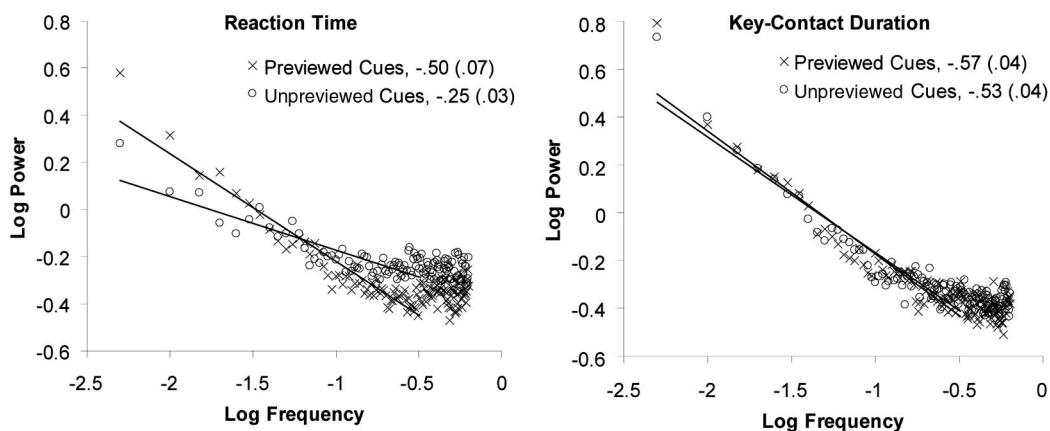


Figure 5. Spectral plots for reaction times (left) and key-contact durations (right) from Experiment 3, each plotted separately for blocks of previewed versus unpreviewed random cue sequences. Average slopes of regression lines are shown with their respective standard errors.

Table 3
Spectral Slope Results for Experiment 3

Measure	Spectral		DFA		Dispersion	
	Prev.	Unprev.	Prev.	Unprev.	Prev.	Unprev.
Reaction times						
<i>M</i>	-0.50	-0.25	-0.47	-0.22	-0.41	-0.22
<i>SE</i>	0.07	0.03	0.07	0.03	0.06	0.02
<i>t</i>		3.58		3.96		3.63
<i>p</i>		.002		.001		.002
Key-contact durations						
<i>M</i>	-0.57	-0.53	-0.53	-0.48	-0.48	-0.45
<i>SE</i>	0.04	0.04	0.03	0.04	0.03	0.03
<i>t</i>		1.05		0.94		0.68
<i>p</i>		.308		.361		.507

Note. *t* and *p* are paired-samples *t*-test results. Spectral = spectral analysis; DFA = detrended fluctuation analysis; dispersion = dispersion analysis; prev. = random and previewed cues; unprev. = random and unpreviewed cues.

were instructed to give each key-press response after each response cue *X* appeared. In the random choice condition, participants were asked to press the left and right keys at random, one key-press response per response cue. Participants were instructed that random meant as if an unbiased coin was flipped to determine the direction of each response.

Experiment 4 Results and Discussion

The methods of data preparation and analysis were the same as in Experiments 1–3. In addition, sequences of responses in the random condition were inspected to ensure that they did not follow any obvious pattern (such as alternating patterns or very long stretches of left or right responses). Analyses indicated that participants were biased to switch responses more often than expected for an independent coin toss. This switching bias is well-established in the literature (see Nickerson, 2002), and it is not relevant for the current purposes, so we did not pursue it further.

Results of the spectral analyses are presented in Figure 6 and Table 4. As in previous experiments, 1/*f* scaling was evident in all conditions. But unlike previous experiments, there was no detectable difference between conditions in spectral slopes for reaction times. As for correlations and means, fluctuations in reaction times and key-contact durations were again apparently independent, as evidenced by the weak correlation coefficients for blocks of random sequences (mean *r* = .07), as well as repeated sequences (mean *r* = .17). Consistent with the fact that neither random nor repeated sequences were perturbed by the response cues, mean reaction times and key-contact durations were comparable between the two sequence types: Mean reaction times were 271 ms and 283 ms for random and patterned sequences, respectively, *t*(1, 17) = .48, *p* > .7. Mean key-contact durations were 114 ms for both types of sequences.

The data again failed to corroborate the repeated behavior account, which predicts that the 1/*f* scaling relation in reaction

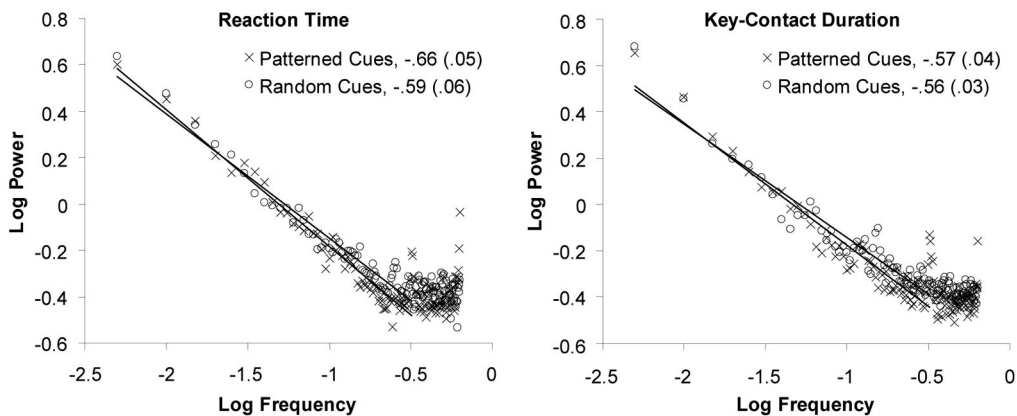


Figure 6. Spectral plots for reaction times (left) and key-contact durations (right) from Experiment 4, each plotted separately for blocks of self-generated patterned versus random cue sequences. Average slopes of regression lines are shown with their respective standard errors.

Table 4
Spectral Slope Results for Experiment 4

Measure	Spectral		DFA		Dispersion	
	Patt.	Rand.	Patt.	Rand.	Patt.	Rand.
Reaction times						
<i>M</i>	-0.66	-0.59	-0.50	-0.49	-0.43	-0.42
<i>SE</i>	0.05	0.06	0.04	0.05	0.04	0.04
<i>t</i>		1.38		0.27		0.17
<i>p</i>		.19		.79		.87
Key-contact durations						
<i>M</i>	-0.57	-0.56	-0.52	-0.50	-0.47	-0.44
<i>SE</i>	0.04	0.03	0.03	0.04	0.03	0.03
<i>t</i>		0.26		0.44		1.11
<i>p</i>		.80		.67		.28

Note. *t* and *p* are paired-samples *t*-test results. Spectral = spectral analysis; DFA = detrended fluctuation analysis; dispersion = dispersion analysis; patt. = self-generated patterned sequences; rand. = self-generated random sequences.

times will weaken in the random choice condition compared with the repeated pattern condition. To the contrary, 1/f fluctuations were equally robust in the two conditions, and the mean spectral slopes were on par with the predictable conditions of Experiments 1–3. This result is consistent with the general association of 1/f scaling with intrinsic fluctuations.

General Discussion

The purpose of the current study was to investigate the relevance of 1/f scaling to cognitive function. Widespread findings of 1/f scaling in cognitive performance call for explanation. We and others have explained 1/f scaling as a fundamental property of how cognitive functions emerge from the coordinated interactions of system components (Gilden, 2001; Kelso, 1995; Van Orden, Holden, & Turvey, 2003). The most prevalent alternative explanation is that 1/f scaling is a byproduct of processes irrelevant to most theories of cognition.

The alternative explanation is the commonly accepted one in cognitive neuroscience. It has been known for some time that “1/f-like noise” is ubiquitous in fMRI measurement series (Aguirre, Zarahn, & Desposito, 1997; Bullmore et al., 2001; Zarahn, Aguirre, & Desposito, 1997). 1/f-like noise is a nuisance to most cognitive neuroscientists because 1/f fluctuations are autocorrelated (due to greater power in lower frequencies) and therefore violate the standard assumption of independent measurements. Much effort has been spent on developing pre-whitening and pre-coloring techniques to work around these autocorrelations (e.g., Bullmore et al., 1996; Friston et al., 1995; Locascio, Jennings, Moore, & Corkin, 1997). By comparison, little effort has been spent on investigating the meaning of 1/f fluctuations in fMRI data.

One reason for this lack of effort is that 1/f scaling is not easily related to the currently dominant paradigm of functional localization. The problem is that 1/f fluctuations appear to pervade the brain, making them uninformative for localizing specific cognitive functions to specific brain areas and mechanisms. Thus the local-

ization paradigm leads one to treat 1/f-like noise in fMRI data as uninteresting to psychological science. This bias leads one to search for non-psychological explanations. For instance, it was found that physical byproducts of neuroimaging can create artifactual 1/f-like noise (Smith et al., 1999) in fMRI measurements. This artifactual source has led some researchers to dismiss 1/f fluctuations altogether as irrelevant to cognition.

However, recent studies have shown that 1/f fluctuations in fMRI measurements are not just artifactual, because their appearance changes as a function of cognitive variables (e.g., C. M. Anderson, Lowen, & Renshaw, 2006; Maxim et al., 2005). Moreover, 1/f fluctuations have been found in electrophysiological measures that are not subject to fMRI artifacts (Bhattacharya, Edwards, Mamelak, & Schuman, 2005; Leopold, Murayama, & Logothetis, 2003; Le Van Quyen, 2003; Linkenkaer-Hansen et al., 2001). So it appears that 1/f fluctuations also originate from neural activity that is relevant to cognitive function, but their expression is obscured in fMRI data by artifactual sources of 1/f-like noise.

In this context, the behavioral measures and manipulations used in the present study are informative. The keyboard and computer produce negligible amounts of noise compared with the strength of the behavioral signal, and the behavioral signal is more transparently related to perceptual, motor, and cognitive function. This transparency enables us to interpret the data as evidence that 1/f scaling is general to the intrinsic fluctuations of cognitive performances. The generality of 1/f scaling makes it difficult to fit within the confines of at least some idiosyncratic accounts, including idiosyncrasies of physiology.

The first such account that we examined was that 1/f scaling has a singular source in cognitive performance. In physiological terms this source might be the multitude of ongoing processes that could combine to impinge on any given measure of behavioral or neural activity. 1/f scaling would be mostly irrelevant to brain and cognitive function if it originates as a coincidence of combining the fluctuations of many non-coordinated processes. However, such multilevel accounts are cast into doubt by the finding of parallel

yet uncorrelated and separately perturbable measurements of $1/f$ fluctuations in reaction times versus key-contact durations.

The second idiosyncratic account that we examined was that $1/f$ fluctuations are peculiar to the repetition of behavioral acts for long periods of time. Repeated acts are used to elicit intrinsic fluctuations, but they may have the unintended consequence of creating iterative, autoregressive maps that produce $1/f$ fluctuations (Beran, 1994; Granger & Joyeux, 1980). However, the hypothesis that $1/f$ fluctuations are created by repetition per se is cast into doubt by the dissociation of $1/f$ fluctuations from repetition in Experiments 3 and 4.

In general our results fail to corroborate the extant idiosyncratic accounts of $1/f$ scaling in cognitive performances. Nonetheless, one may still claim that, for some unknown reason, controlled and automatic processes separately produce $1/f$ fluctuations in reaction times and key-contact durations under conditions of intrinsic fluctuation. As slippery as this claim is, we can show it to be problematic given the data. The problem is that the association of reaction times with controlled processes entails an association of $1/f$ scaling with higher "cognitive workload" relative to automatic processes. This association forces one to predict a consistent relationship between $1/f$ scaling and workload, but the results to date are contradictory in this regard.

To start with, the results from Experiments 1–3 suggest that the $1/f$ scaling relation is relatively weakened under high workload, assuming that unpredictable cues require attentive responses and greater workload compared with predictable cues. However, this relationship was contradicted in Experiment 4 because the $1/f$ scaling relation was *not* weakened when participants simulated unpredictable responses. Simulating randomness has been shown to be a high workload task (Baddeley, 1996; Gilhooly, Logie, & Wynn, 1999; Oomen & Postma, 2002; Vandierendonck, De Vooght, & Van der Goten, 1998), arguably even higher than responding to unpredictable cues.

The workload explanation is made even more tenuous when we consider an experiment in which Chen and his colleagues (Chen, Ding, & Kelso, 2001; see also Ding, Chen, & Kelso, 2002) examined tapping data for $1/f$ scaling. The data consisted of timing errors compared to a metronome that sets the pace for tapping. Timing errors were subjected to spectral analysis, and different power spectra were observed for syncopated versus synchronized tapping. Syncopated tapping, between the beats of a metronome, yielded more robust $1/f$ scaling than synchronized tapping, which is on the beat. Chen et al. (2001) attributed the steeper slope to the increased task difficulty of tapping between the beats. Thus, apparently, more difficult tasks may yield clearer signals of $1/f$ scaling and less difficult tasks may yield clearer signals of $1/f$ scaling (Experiments 1–3; see also Clayton & Frey, 1997; Gildea et al., 1995; Wagenmakers et al., 2004; Ward, 2002), and task difficulty may have no effect on the appearance of $1/f$ scaling (as we found in Experiment 4). We can conclude only that there is no apparent association between a dimension of controlled or strategic processing and $1/f$ scaling (see also Van Orden, Moreno, & Holden, 2003).

Of course we cannot rule out all possible accounts that would assign structurally and functionally distinct sources of $1/f$ scaling to reaction times versus key-contact durations; there are far too many to count let alone test. The challenge is not to create an ad hoc account for every new observation of $1/f$ scaling (that can

always be done). For instance, it is no problem to simply state that $1/f$ memory traces are laid down for all intrinsic fluctuations. The problem with this kind of account is that it gives no insight into the phenomena. It leaves one with the challenge of formulating a general theory to answer the question of why.

Toward Theories of Emergent Cognitive Function

According to emergent coordination, $1/f$ scaling is not restricted to some domain-specific process or measure of cognition. Nor is it a widespread byproduct of physiology that is irrelevant to cognition. $1/f$ scaling is instead a general property of metastability (Bak, Chen, & Creutz, 1989; Kelso, 1995; Usher et al., 1995). Metastability emerges when interactions among the components of a system are balanced between two extremes. One extreme is weak component interactions that cannot support coordinated patterns of activity across components. The other extreme is strong interactions that do not allow patterns to flexibly reorganize in response to changing conditions.

In this theoretical framework, cognitive functions emerge as metastable patterns of neural and bodily activity. Unlike the fixedness of hard-coded algorithms that reside in isolable locales of neural hardware, the flexibility of metastable patterns makes them exquisitely and inherently sensitive to context (Bressler & Kelso, 2001). Thus cognitive functions are theorized as being inherently defined by their task parameters, environmental constraints, and so on. The continuous unfolding of metastable patterns creates intrinsic fluctuations that universally exhibit the $1/f$ scaling relation. As conditions deviate from intrinsic fluctuation, patterns are increasingly shaped by whatever context-specific factors are responsible for the deviations.

Context-specific factors must therefore be minimized or removed from measurements in order to reveal the generic $1/f$ signature of metastability. However, by focusing on intrinsic fluctuations in the current study, we certainly do not mean to belittle the importance of metastable patterns that are shaped by context-specific factors. Indeed these are the cognitive performances hypothesized to emerge from the generic, scale-invariant state of metastability.

Take speech, for instance. Speech production appears to be metastable in that, at any given time, many different articulations are simultaneously available and ready to be produced. Short articulatory patterns like those associated with individual phonemes emerge and submerge over the course of tens of milliseconds, whereas longer patterns (consonant clusters, syllables, etc.) emerge and submerge over longer timescales. Each articulatory degree of freedom must maintain its identity while simultaneously playing different roles across different speech gestures.

Decades of speech research has shown that phonemes are intimately and inextricably defined by the contexts of their articulatory and acoustic expressions (e.g., via coarticulation and assimilation; Fowler & Saltzman, 1993). Therefore, measures of running speech reflect these context-specific effects as variations that are particular to the utterances being measured. To measure the generic signature of metastability that underlies the context-specific patterns of articulatory gestures, one must measure fluctuations that are not specific to any particular speech context. Such context-general fluctuations can be measured by holding context as constant as possible from one measurement to the next.

For speech this means instructing a participant to repeat an utterance many times in order to elicit intrinsic fluctuations from one utterance to the next. G. Anderson and Kello (2006) did just that by instructing participants to repeat the word *bucket* many times. The authors took over 100 acoustic measures of each word utterance and analyzed the fluctuations in those measures from one *bucket* to the next. Across 10 participants, every single measure was found to fluctuate in the 1/f scaling relation, including dozens of parallel yet uncorrelated 1/f fluctuations.

The findings of 1/f scaling throughout the intrinsic fluctuations of speech, and in two key response measures in the current study, are parsimoniously explained by emergent coordination and its theoretical basis in metastability: 1/f scaling is prevalent wherever intrinsic fluctuations are measured, and less so wherever measurements are perturbed. In fact, to our knowledge, all measures to date of 1/f scaling in brain and behavior have been more or less taken under conditions of intrinsic fluctuation. This has even been shown for neural activity (Linkenkaer-Hansen, Nikulin, Palva, Kaila, & Ilmoniemi, 2004).

1/f scaling is the focus of the current study, but it is not the only source of evidence for metastability and emergent coordination. The anatomical organization of the human nervous system may generally be characterized by a balance between *segregation* and *integration* of neural pathways (Tononi, Sporns, & Edelman, 1994). This balance is thought to allow cortical and subcortical areas to maintain some locality of processing while at the same time participating in globally coordinated patterns of activation. In other words, the balance of segregation and integration may allow metastable patterns to form (Sporns, 2004). This notion is supported by a model that generates metastable patterns of activity at the balance of segregating and integrating pathways (Friston, 1997) and by electrophysiological data resembling metastable patterns in neural activity (Fingelkurts & Fingelkurts, 2004; Freeman & Holmes, 2005).

More generally, metastability provides a useful framework for theorizing about brain and cognitive function. For instance, it provides tools that may help conceptualize, and eventually formalize, the brain's ability to reorganize and reimplement functions after losing neural tissue due to trauma or disease. Recall von Holst's (1939/1973) centipede and its ability to reimplement the function of locomotion after losing some number of legs. Locomotion is accomplished using modes of coordination that are appropriate to the remaining number of legs, even though the centipede does not appear to have separately stored motor programs for these modes. They are instead inherent to the structural and dynamical relations among components of the centipede's anatomy and physiology. Metastability may help to relate the centipede and other biological models of emergent coordination with the development and recovery of brain and cognitive function.

It also appears that the 1/f scaling signature of metastability is associated with healthy physiological and cognitive function. The healthy, resting heart exhibits 1/f scaling in its intrinsic fluctuations as measured in series of inter-beat intervals (Goldberger, 1990; Goldberger, Rigney, & West, 1990). The same is true for healthy, self-paced walking in terms of inter-stride intervals (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995; Ivanov, Rosenblum, et al., 1998; Viswanatha, Peng, Stanley, & Goldberger, 1997). However, inter-beat intervals deviate from the 1/f scaling relation

for the elderly and patients with pathological heart conditions (Peng, Havlin, Hausdorff, et al., 1995), and inter-stride intervals similarly deviate for the elderly and patients with movement disorders (Hausdorff et al., 2001, 1997). More recently it was found that fluctuations in fMRI measurements of resting state activation for Alzheimer's patients deviate from the 1/f scaling relation (Maxim et al., 2005). All together, these findings suggest that metastable patterns of activity are a sign of functionally effective and robust coordination.

The next step is to develop theories and models of specific cognitive functions that are formulated as emergent, metastable patterns of coordination. One direction to take is to investigate whether there is computational power in metastability that is of use to cognitive function and possibly other biological functions as well. For instance, Kwok and Smith (2005) built a self-organizing neural network to solve combinatorial optimization problems like the famous traveling salesman problem. The model had a parameter that governed the order and disorder of component activities, and model performance was optimal when this parameter was set at the critical point between ordered and disordered phases. The metastable patterns that emerged near this point enabled the model to more effectively search the problem space for globally optimal solutions. Metastability also produced 1/f fluctuations in the model's component activities. Although it remains to be seen whether this model will prove to be useful in developing simulations of cognitive function, the work demonstrates the computational power of metastability and the functionality of emergent coordination.

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