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The Effect of Cue Predictability on Long-Range Dependencies in Response Times versus Response Durations

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Abstract

Two experiments were conducted in order to test the effects of cue predictability on serial dependencies in response times and response durations. Predictability in the timing (Experiment 1) and identity (Experiment 2) of response cues was manipulated. Results of both experiments showed that long-range dependencies in response times were stronger when cues were predictable versus unpredictable. By contrast, long-range dependencies in response durations were unaffected by cue predictability. Results are discussed in light of five hypotheses about the source of long-range dependencies in human behavior.

Introduction

In most psychological experiments, the variability in human behavior is divided into two categories: some variations in measurement are explained by the experimental factors, and other variations are not. The latter category is often termed *error variance*, and it usually does not play a role in theorizing about the psychological processes under examination. One reason why researchers ignore error variance is because they often assume that it is effectively random, or possibly the product of mundane factors such as practice, fatigue, or perseveration. These assumptions lead one to think of error variance as uninformative or, at best, irrelevant.

A growing body of experimental results has recently prompted some researchers to pay closer attention to the ostensibly random fluctuations in human behavior. It appears that, contrary to popular belief, these fluctuations tend to exhibit patterns that persist over time. A transparent way to think about these patterns is through the *autocorrelation* function. Suppose that X_t is a time series of measurements taken from a participant in an experiment. The autocorrelation of this time series is defined as (Wagenmakers, Farrell, & Ratcliff, in press),

$$C(k) = \frac{E[\{X_t - \mu\}\{X_{t+k} - \mu\}]}{E[\{X_t - \mu\}^2]},$$

where $E[]$ is expected value, μ is the mean of X_t, and k is some number of measurements between the time series and an offset copy of itself.

If measurements are strictly independent of each other, then $C(k)$ is zero for all $k > 0$. The time series is not correlated with itself at any offset, and hence, there are no persisting patterns in the fluctuations. This condition is often referred to as *white noise* (see top series in Figure 1), and it is common to assume that error variance is some type of white noise (e.g., Gaussian). However, it turns out that measurements of human behavior are often not characterized by white noise. Instead, they exhibit serial dependencies such that $C(k)$ is positive for some $k > 0$.

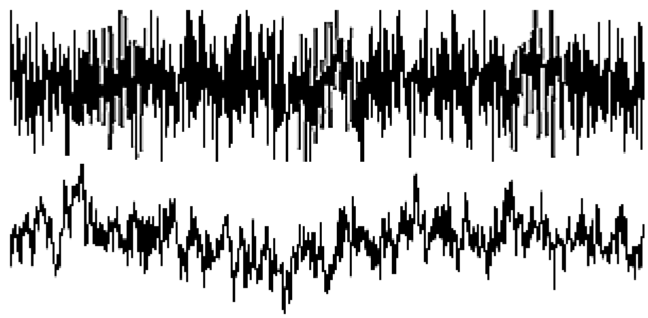

Figure 1: Illustrations of white noise (top) and pink noise (bottom; from Gilden, 2001).

Serial dependencies have been found in a wide variety of human behaviors (for a review, see Van Orden, Holden, & Turvey, 2003). With respect to the study of perception and cognition, serial dependencies have been found in experiments on mental rotation (Gilden, 1997), lexical decision (Gilden, 1997), perceptual learning (Wagman, Dahle, & Schmidt, 2002), simple reaction time (Ward & Richard, 2001), and visual search (Aks, Zelinsky, & Sprott, 2002).

A major question about these findings concerns the kind of dependencies that were observed. The authors of these studies interpreted their findings as evidence for a particular kind of serial dependency often referred to as *long-range dependency,* of which *1/f noise* or *pink noise* are special cases (see bottom series in Figure 1). In a long-range dependent series, $C(k)$ is positive and decreases as a power of k,

$$C(k) = |k|^{-\gamma}, \qquad 0 < \gamma < 1.$$

Long-range dependency is of special interest because it appears to be ubiquitous in nature (see Van Orden et al., 2003), and it has some intriguing properties such as fractal structure, i.e., a change in the time scale of measurement does not affect the distributional properties of a long-range dependent time series. Long-range dependencies have motivated a number of general theories about the sources of fluctuations in human behavior, and these theories were the focus of the current experiments.

However, before the theories are addressed, it must be noted that long-range dependencies can be difficult to distinguish from *short-range dependencies*, in which *C(k)* decreases exponentially with *k* (Wagenmakers et al., in press),

$$C(k) = \phi_1^{|k|},$$

where $-1 < \Phi_1 < 1$. Although *C(k)* declines more quickly in short-range dependent series compared with long-range dependent series (hence their names), the difference in rates of decline can be rather small. Nonetheless, short-range dependent series have very different properties (e.g., they can be generated by simple autoregressive processes), and they lead to different kinds of theories about fluctuations in human behavior. Therefore, Wagenmakers and his colleagues argued that empirical tests of long-range dependency must treat short-range dependency, rather than white noise, as the null hypothesis. Using this more stringent criterion, Wagenmakers et al. still found long-range dependencies in measurements of human behavior under a variety of experimental conditions. Their findings and analyses confirm that long-range dependency is a real phenomenon.

Explanations of Long-Range Dependence

Why do fluctuations in human behavior exhibit long-range dependencies? Only certain kinds of processes are known to produce long-range dependencies (for a review, see Wagenmakers et al., in press). The ostensibly special status of long-range dependencies has prompted researchers to search for general properties of human behavior that might explain their source(s). Here we review five explanations that have been offered.

Three Time Scales. Any specific observation of long-range dependence can be mimicked mathematically by the combination of three sources of white noise that operate on different time scales, each scale separated by an order of magnitude. In the context of perceptual and cognitive processes, Ward (2002) has suggested that unconscious, preconscious, and conscious processes may be three such sources of white noise whose combination is observed in fluctuations of human behavior.

While the transparency of this explanation is appealing, it is somewhat brittle because any three particular scales of white noise will mimic long-range dependence *only* for a single, particular scale of measurement (see Van Orden et al., 2003). What this means is that three-scale accounts must be fit to data posthoc. By contrast, true long-range dependence exists over all scales of measurement (within the limits of the system in question) due to its fractal structure. Long-range dependence in human behavior has, in fact, been found across a range of scales of measurement (for a review, see Van Orden et al., 2003).

Many Short-Range Dependencies. Granger (1980) showed that, under certain circumstances, the summation of many short-range dependent series can produce a true long-range dependent series. Ding, Chen, and Kelso (2001) proposed that long-range correlations found in timing tasks (and, by extension, in other kinds of tasks) may be the result of such summations. Their argument was based on the premise that cognitive processes are supported by large-scale networks of neural processes. Ding et al. reasoned that, in at least some cases, such neural networks will be characterized by large sets of short-range dependent processes. If the timing of behavior is driven by the summation of these processes, then fluctuations in timing will exhibit long-range dependence.

Ding et al. (2001) made the further statement that more difficult tasks require larger numbers of short-range dependent processes. This statement leads to the prediction that long-range dependencies will be stronger in more difficult tasks. In support of this prediction, they reported two timing tasks in which participants were asked to match their rates of tapping with the beat of a metronome. In one condition, participants were asked to tap in synchrony with the metronome. In another condition, participants were asked to tap at the midpoint between each pair of beats (i.e., to syncopate). Syncopation is a more difficult tapping task (e.g., less stable; see Kelso, DelColle, & Schner, 1990) compared with synchronization, and fluctuations in syncopated tapping exhibited stronger evidence of long-range dependence compared with synchronized tapping.

Mental Set. Gilden (2001) proposed that experimental tasks whose demands are relatively consistent across trials invoke a "mental set" in the participant. Gilden's definition of mental set entailed the repeated formation of mental representations necessary to perform the task. When the task is consistent, Gilden proposed that a dynamic of memory is created by this repetition such that memory components interact on multiple time scales. Under some circumstances, interactions of this nature have been shown to generate long-range dependencies (e.g., see Jensen, 1998).

Gilden (2001) left the nature of his proposed memory components unspecified, but his hypothesis was nonetheless formulated in sufficient detail to make a testable prediction. If mental set is broken by sudden changes in task demands, then the hypothesized dynamic of memory would not have an opportunity to form, and long-range dependencies in response fluctuations should disappear. Gilden tested this prediction by measuring series of reaction times to color or shape discriminations when each of these tasks was blocked, compared with a mixed condition in which participants had to switch between tasks across trials. Gilden found evidence of long-range dependence in the blocked conditions, but not the mixed conditions. These findings were consistent with his mental set explanation of long-range dependence.

Strategy Shifts. By definition, a long-range dependent series is stationary in the sense that its distributional characteristics do not change over time. However, a long-range dependent series can be difficult to distinguish from some kinds of non-stationary series that go through changes in their distributional characteristics over time.

It is probably true that any given experimental task can be performed in a number of ways, despite any and all efforts to make the task demands as explicit and precise as possible. If each means of performing a task is termed a "strategy", then it is very possible that a participant will change his or her strategy for performing a task over the course of an experiment. If strategy shifts occurred repeatedly over the course of measurement, they would have the potential to mimic long-range dependence. Wagenmakers et al. (in press) presented a computational demonstration of how strategy shifts (shifts in response criteria, in this case) can create non-stationary fluctuations in response times that mimic long-range dependencies.

Interaction-Dominant Dynamics. Van Orden et al. (2003) proposed that, at a very general level, humans are composed of many component processes that all interact on multiple time-scales. Their proposal was based on the fundamental idea that the structure and complexity seen in human behavior is a phenomenon of self-organization, and that self-organizing systems are ones that have interaction-dominant dynamics. They argued that it is these dynamics, intrinsic to human beings (and many other types of systems), that give rise to long-range dependencies in human behavior.

As general as they are, the ideas put forth by Van Orden and his colleagues (2003) lead to a testable prediction. If long-range dependence is the intrinsic signature of self-organization in human behavior, then any perturbations to behavior caused by external factors should disrupt the intrinsic dynamics, thereby obscuring their signature. Van Orden et al. argued that the results to date on long-range dependencies in human behavior (e.g., as cited in the other explanations listed here) are consistent with this prediction.

Current Experiments

Two experiments are reported here that were designed to explore a factor that was predicted to modulate the degree of long-range dependence in RT fluctuations. The factor was motivated by the explanations just listed. In particular, we tested whether sources of variability *external* to the participant would reduce the degree of long-range dependence in fluctuations of human behavior. Key presses were the measured behaviors, and sources of external variability were manipulated by the degree of *cue predictability*.

In Experiment 1, predictability in the timing of response cues was manipulated to be either completely predictable or completely unpredictable. When cues were predictable, fluctuations in response times were driven primarily by the participant. The cues themselves had little bearing on behavior because they were entirely redundant; participants knew that the next cue would always appear one second after the previous response (see Methods section). By contrast, when the timing of cues was unpredictable, the timing of responses had to be driven primarily by the cue itself, rather than any expectancies internalized by the participants.

If long-range dependence is internal to human behavior, then external variability should mask it. This idea is consistent with some previous explanations of long-range dependence (see Discussion section). This idea also leads to a further prediction that is quite counterintuitive. Participants were asked to press a key as soon as they perceived a cue. Thus, the task demands were satisfied when the finger moved down and the key made contact with its sensor. The task made no demands on when participants should lift their finger off the key. Therefore, fluctuations in the *durations* of key presses should be free to reflect internal variability, provided that the timing of the downward motion can be dissociated from timing of the upward motion. If so, we should observe *no* effect of predictability on the degree of long-range dependency in response durations.

In Experiment 2, sources of external variability were introduced by a different means. The *identity* of cues, instead of the timing of cues, was manipulated to be predictable or unpredictable. Two different cues signaled two different responses. Cue identity was made predictable or not by giving a preview or not of each upcoming cue. Analogous to the manipulation of predictability in Experiment 1, the preview manipulated the degree to which behavior was driven by the cues themselves, versus expectancies about the cues.

Experiment 1

Participants. Eighteen participants were recruited for the experiment. Sixteen were undergraduates who participated for course credit, and two were graduate students who were compensated for their participation.

Procedure. Each participant saw one block of predictable cues and one block of unpredictable cues, with block order counterbalanced across participants. Participants were instructed to press the space bar with their dominant hand as quickly as possible every time they saw an "X" flash on the screen. Demonstrations and practice blocks were given before each experimental block. Participants were instructed to wait till they saw an "X" before responding; if they pressed the space bar before a cue appeared, they heard a warning tone. Each block consisted of 1100 cues and took about 25 minutes to complete. The experimenter stayed in the room with the participant throughout the experiment. Participants took a short break between blocks.

Participants were seated about two feet away from a CRT monitor, and each cue appeared for about 50 ms in the center of the screen in Times New Roman font. A pair for visual flankers appeared immediately following each cue, and remained on the screen until the participant pressed the space bar. The flankers provided a redundant cue that the computer was awaiting a response (in case the participant missed a cue by accident).

Each subsequent cue was timed relative to the previous response. In the predictable condition, the next cue always appeared 1 s after the previous response was given. In the unpredictable condition, the timing of the next cue was sampled randomly from an exponential distribution with a mean of 1 s, a minimum of 1 ms and a maximum of 12 s. The exponential distribution was used because it has a flat hazard function, which means that the probability of receiving a cue was constant as a function of wait time (Simpson et al., 2000). The time from cue to key press was recorded (response time), as well as the length of time that participants pressed each key (response duration).

Results

To illustrate the time series structures that were typically observed, the series of response times for one participant in the predictable and unpredictable conditions are shown in Figure 2. The series of response durations for this participant are shown in Figure 3.

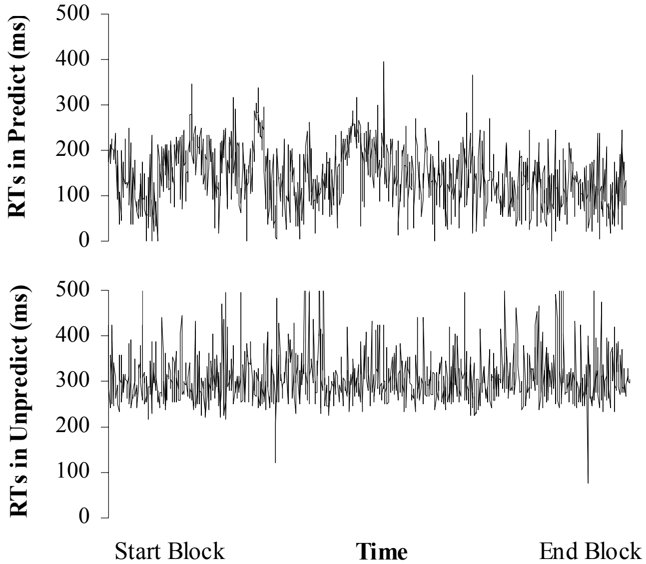

Figure 2. Response times for one participant in the predictable (top) and unpredictable (bottom) conditions of Expt 1 (responses above 500 ms have been truncated).

Averaged across participants, the percentage of anticipatory responses was 1.99% in the unpredictable condition, and 3.9% in the predictable condition. All anticipatory responses were removed from the analyses. The mean correlation of response times with response durations was r = .02 in the unpredictable condition, and r = -.21 in the predictable condition.

Spectral analyses are standardly used to measure the degree of long-range dependence in a time series, and we adopted the method of spectral analysis described by Holden (unpublished; also see Gilden, 1997). In particular, outliers were first removed from each time series (values > 1000 ms or outside 3 SDs of each participant's mean for each measure in each condition). Then, linear and quadratic trends were removed to avoid dependencies caused by practice or fatigue. A power spectrum was then computed over 1024 of the remaining data points, and log frequency was regressed against log power. The slope of this regression line in log-log coordinates was used as a measure of serial dependence: more negative slopes correspond to stronger degrees of serial dependence.

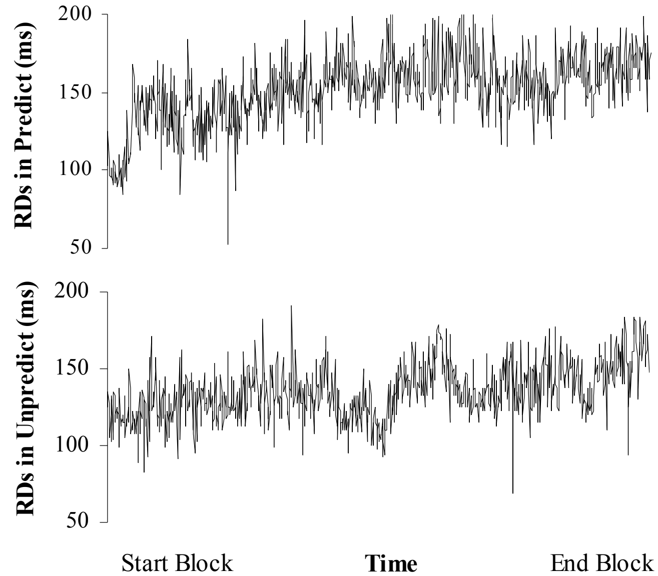

Figure 3. Response durations for one participant in the predictable and unpredictable conditions of Expt 1.

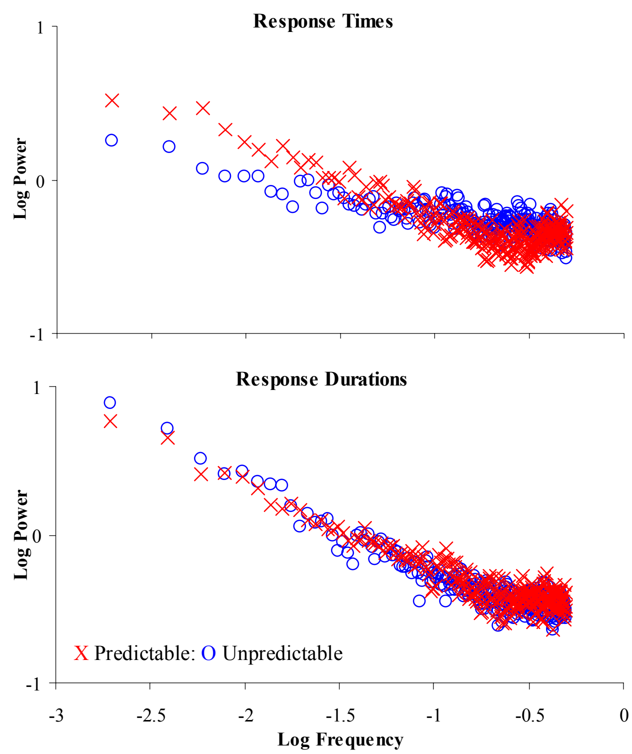

Figure 4. Aggregate spectral plots for Expt 1.

The aggregate power spectra, averaged across participants for each condition, are plotted in Figure 4. For response times, slopes in the predictable condition were reliably more negative than slopes in the unpredictable condition, $t(17)$= 4.26, $p < .001$. For response durations, there was no reliable difference in slopes, $t(17) < 1$. Moreover, slopes for response durations were reliably more negative than slopes for response times, $t(35) = 7.21$, $p < .001$.

Experiment 2

Participants. Eighteen undergraduates participated in the experiment in exchange for course credit.

Procedure. The procedure was identical to that used in Experiment 1, except for the following changes. The response cue was either '>' or '<', and participants were instructed to press the right arrow key for the former, and the left arrow key for the latter. Flankers appeared on either side of the response cues as signals to respond, and the flankers always appeared 1 s after the previous response was given. In the preview condition, the next response cue always appeared immediately following the previous response; thus, participants had 1 s to process the cue and prepare their response. In the no-preview condition, each cue appeared in conjunction with its signal to respond; thus, participants had to process the cue and choose their response as quickly as possible.

Results

Averaged across participants, the percentage of anticipatory responses was .03% in the unpredictable condition, and .45% in the predictable condition. The percentage of errors was .80% and .27%, respectively. All anticipatory responses were removed from the analyses, but the few errors were retained. The mean correlation of response times with response durations was $r = .05$ in the unpredictable condition, and $r = -.08$ in the predictable condition.

The aggregate power spectra are plotted in Figure 5. For response times, slopes in the predictable preview condition were reliably more negative than slopes in the unpredictable no-preview condition, $t(17) = 2.31$, $p < .05$. For response durations, there was a small but unreliable difference in slopes, $t(17) = 1.80$, $p < .09$. Moreover, slopes for response durations were reliably more negative than slopes for response times, $t(35) = 3.55$, $p < .001$.

Discussion

Two experiments were reported in which long-range dependencies were measured as a function of cue predictability. Results showed greater degrees of dependency in series of response times when the cues were predictable, both in terms of timing and identity. By contrast, results showed large and comparable degrees of dependency in all series of response durations. The observed dissociation between response times and response durations was consistent with the idea that external sources of variability mask the long-range dependence that is intrinsic to human behavior.

It also appeared that the effect of predictability in cue timing (Experiment 1) was stronger than that in cue identity (Experiment 2), albeit further experiments are necessary to bear this out. One possible explanation is unpredictable timing introduces more external variability compared with unpredictable choice responding. However, to test this explanation, one would need to develop a more explicit means of parsing internal and external sources of variability.

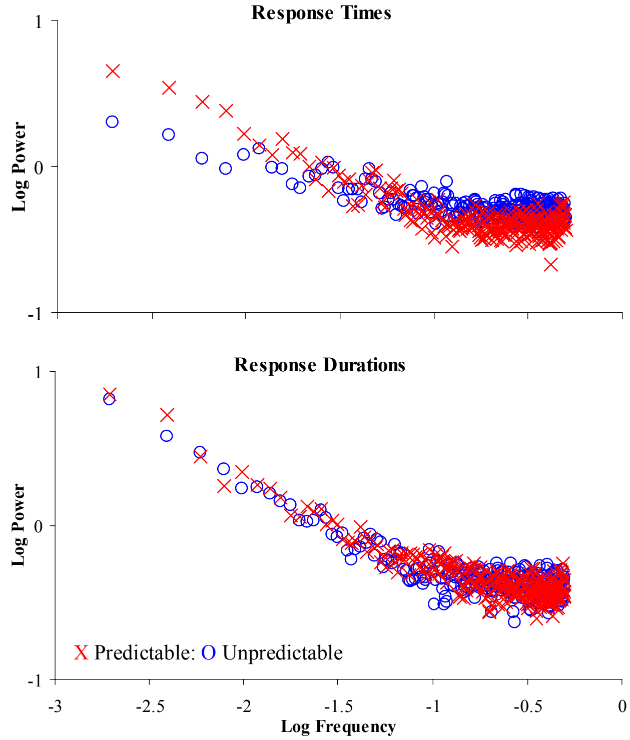

Figure 5. Aggregate spectral plots for Expt 2.

It is important to note that the hypothesis of long-range dependence was not explicitly tested against the short-range alternative in the current data. We did not conduct these tests because the IDD predictions could be tested without them. However, the long-range/short-range distinction is important, and we plan to address this issue in future work.

How do the current results bear on the five explanations of long-range dependence outlined in the Introduction section? We address this question here for each explanation in turn.

Three Time Scales. Sources of white noise on three different time scales could be used to mimic the long-range dependencies (or lack thereof) for each participant in each condition of the two reported experiments. However, these parameter fits would be posthoc, and they would offer no insight into the differences in degree of long-range dependence between experimental conditions.

Many Short-Range Dependencies. As noted earlier, this explanation leads one to predict that greater degrees of long-range dependence should be found in more demanding tasks. The unpredictable conditions were clearly more demanding because their mean RTs were much greater. However, the unpredictable conditions showed *lesser* degrees of long-range dependence compared with the predictable conditions. Moreover, summations of short-range dependencies appear to offer no insight into the observed differences in dependencies between response times and response durations.

Mental Set. Gilden (2001) proposed that long-range dependencies should be weaker when a person's mental set is repeatedly broken or interrupted. One could imagine that participants were able to maintain a more stable mental set in the predictable conditions compared with the unpredictable conditions, which would make the current results consistent with the mental set explanation. It is less clear how the mental set explanation would apply to the differences in long-range dependence between response times and response durations. One would presumably have to propose that these behaviors are governed by different mental sets, but given the close physical relationship between a button press and its release, the idea of different mental sets seems implausible. The bottom line is that the mental set explanation is not yet formulated to the point where it might offer insight into the current results.

Strategy Shifts. Wagenmakers et al. (in press) conjectured that participants might be more apt to shift strategies, and therefore exhibit long-range dependencies in their behaviors, when they are bored. Participants were almost certainly bored in all of the current experimental conditions, but one could argue that the predictable conditions were more boring than the unpredictable ones. If so, the finding that long-range dependencies in response times were stronger in the predictable conditions is consistent with the strategy shifts explanation. However, one would have to apply this explanation to response durations as well, and there was no such effect on long-range dependencies in this measure. It remains to be seen whether a strategy shift explanation could be made to account for these results.

Interaction-Dominant Dynamics. This explanation states that long-range dependencies come from the interdependent dynamics that underlie the self-organization of human behavior. These dynamics are hypothesized to be perturbed by external forces. If sources of external variability are thought of as external forces, then all the results reported herein are consistent with the interaction-dominant dynamics explanation. Predictability was a force on response times, but not response durations, because the task made demands on the former but not the latter.

In conclusion, the current results are, for the time being, most consistent with the interaction-dominant dynamics explanation. Of course, these explanations are all in their infancy; it would be an overstatement at this point to refer to them as theories. Be that as it may, the results were clear and far from trivial to explain. We believe that further empirical and theoretical investigations into the sources of long-range dependence in human behavior will prove to be valuable to studies of perception and cognition.

Acknowledgments

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