*Research Article*

# Response Variability in Attention-Deficit Disorders

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ABSTRACT—***Reaction times in a mental rotation task were measured across a diverse population that sorted into two groupings based on overall variability. Although both the low- and the high-variance groups produced data that displayed the trends typical of mental rotation, the two groups' reaction time sequences had very different autocorrelation functions. Power spectra derived from the two groups' data showed the presence of distinctive noise processes with long memory. Normal levels of variance were associated with 1/f noise, whereas high-variance data had substantial traces of random walk contour. These findings provide new perspectives on cognitive assessments of attention dysfunction.***

In a recent review article on the neuroscience of attention-deficit/hyperactivity disorder (ADHD), Castellanos and Tannock (2002) remarked that "[high] response variability is the one ubiquitous finding in ADHD research across a variety of speeded-reaction time tasks, laboratories, and cultures" (p. 624). This is an observation of some importance, and it is of both practical and theoretical interest to understand what high response variability entails and, for that matter, what it means. It means more than large variance. The distributions of speeded reaction time (RT) are positively skewed, and Castellanos and Tannock's comment could refer to a fatter midsection, to a more distended tail, or to both, as Hervey (2004) found. High response variability may also have implications that extend beyond the distributional properties of RT. RTs are almost always collected in large blocks of trials, and within blocks the natural ordering of trials generates a kind of historical record. The RT records of normal adults have a characteristic structure (Gilden, 1997, 2001; Thornton & Gilden, 2005; Van Orden, Holden, & Turvey, 2003, 2005), and this manner of conceptualizing RT may be of some relevance for understanding ADHD data.[1]

It is now well established that RT sequences in normal adults often show evidence of a long-term memory process known as 1/*f* noise (Gilden, 2001; Thornton & Gilden, 2005), so named because its power spectrum falls inversely with frequency. This kind of noise is found in that part of the data generally regarded as unexplained variance, the trial-to-trial residual variability. Although residual variability is not usually the focus of interest in experimental studies, the amplitude of 1/*f* noise may easily exceed that of the treatment effects. In typical cognitive tasks, the 1/*f* noise component may account for 30 to 40% of the variance when the treatment effects explain only about 10% (Gilden, 1997, 2001). The correlational structure of 1/*f* noise gives it weak predictability, intermediate between that of white noise and random-walk noise. In fact, the pitch and loudness contours in speech and music are examples of 1/*f* noise (Voss & Clarke, 1975, 1978). It has attained a certain mystique in the physical and biological sciences because it manages to be both rare and ubiquitous. Examples of 1/*f* noise are found in quasar luminosity, tide and river height, traffic flow, and human heartbeat (Handel & Chung, 1993; Press, 1978). There is no definite interpretation of what 1/*f* noise signifies, but systems exhibiting it often have a dynamic that incorporates aspects of both ordered and disordered flow. The question of whether such systems have anything deeper in common is itself controversial (Milotti, 2002), but several general mechanisms have been

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[1]Castellanos et al. (2005) analyzed RT sequences using Fourier techniques. These authors found evidence for a wave with a period of 20 s in the RT histories of ADHD male children, ages 6 through 12, in an Eriksen flanker task. In the data presented here, there is no evidence for a spike in the spectrum at a particular frequency. We have not analyzed data from children, nor have we conducted an analysis of residual latencies in the Eriksen flanker task. Perhaps the differences between our results and those of Castellanos et al. stem from the subject population or task. Although this is not the place for a detailed review, we believe there may be artifacts in the analysis of Castellanos et al. Their trial blocks consisted of only 60 trials, an insufficient number for abstracting detailed and statistically reliable spectral structure. Furthermore, the spectrum depicted for a control subject does not look even remotely like the spectra published for normal adults, and if the critical difference between studies is not age, it must be the method of analysis.

  

proposed to account for its ubiquity (Bak, 1990, 1992; Bak, Tang, & Wiesenfeld, 1987; West & Shlesinger, 1989).

Although it is not yet clear what 1/*f* noise means, there is little question that it is a general property of choice behavior, including speeded judgment, signal detection, and matching to sample (Gilden, 2001; Gilden, Thornton, & Mallon, 1995). This type of noise may be the signature of a healthy nervous system. It is in this light that high-variability (HV) choice RT data become interesting. The processes that create large variation in RT will influence the internal correlations, most likely whitening them. What the spectrum of HV data looks like is unknown, as such data are not commonly encountered in the normal undergraduate subject pools, and ADHD researchers typically do not take a time-series perspective on their data.

## RT SEQUENCES

The literature on ADHD in adults does not prepare the naive investigator for the type of data that ADHD observers generate in RT paradigms. In the course of negative-priming assessments (Shin, 2005),[2] we first became aware of the properties of ADHD RT data that had not been discussed in published work. Our studies were originally designed to measure the time course of negative priming in persons with various subtypes of ADHD, and they were based on tasks commonplace in the literature (Hasher, Zacks, Stoltzfus, & Kane, 1996; Neill, Lissner, & Beck, 1990). As we ran the studies, we became aware that some of the data were quite unusual. Figure 1 shows example RT histories for a task that involved determining if the second and fourth letters in a five-place letter string were the same or different. In this RT study, the observers were instructed to respond as quickly as possible without making too many errors. The bottom panel is an example of typical data from an undergraduate, and the top panel shows the data produced by an unmedicated adult diagnosed with the combined type of ADHD. Not all of the data from our ADHD observers were so divergent, but we frequently saw data of this type, and such data made interpretation of the group differences in negative priming difficult.

The ADHD data in Figure 1 are unusual in a number of ways. Obviously they have a much larger variance than "normal" data. The standard deviation of the normal data is about 100 ms, typical for this task. The standard deviation of the ADHD data is three times larger. But more important from our perspective are the large hills and valleys in the time series of the ADHD data. This observer seems to be cycling through some kind of process that is continuously interrupted by large and random perturbations. This picture is testimony to the benefits of viewing data as a time series and not as a distribution. The time-series perspective motivates spectral analysis of ADHD data and a corresponding investigation into the kinds of noise produced by ADHD populations.

[2]These experiments were conducted in dissertation research supervised by one of the authors (Gilden) and by Caryn Carlson.

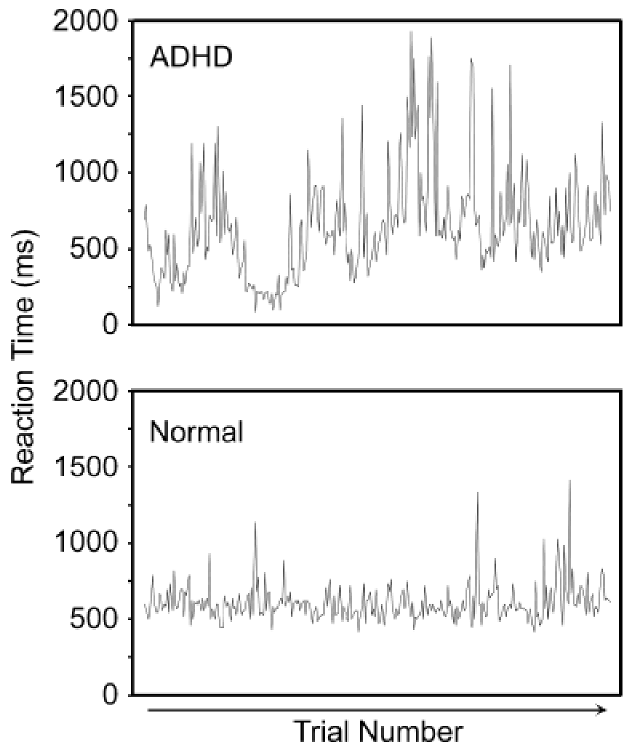


**Fig. 1.** Reaction time sequences from 2 observers who were deciding if the second and fourth letters in a five-letter string were the same or different. The sequences are the exact records of the trial-by-trial reaction times. The sequence at the top was produced by an observer diagnosed with attention-deficit/hyperactivity disorder (ADHD), and the sequence at the bottom was produced by a typical undergraduate.

## AN EXPERIMENT INVITING HV DATA

RT data with high variability are an odd thing to study insofar as one has to wonder what the RTs mean. The nominal laboratory practice in speeded-response paradigms is to use young adults who display vigilance, stamina, and speed. In this case, the RTs are considered to reflect a chain of processes: perceptual analysis, response mapping, and response execution (Pashler & Johnston, 1998). Although HV data might also arise from the chaining of these processes, it seems likely that the frequent large RTs in such data are an indication of intrusions associated with loss of vigilance (becoming lost or distracted). If the episodes of inattention are randomly interspersed in the trial sequence, then they might not distort the underlying patterns created by the normal execution chain. In terms of cell means, data with episodes of inattention might then be characterized as simply being slower and more variable than data without such episodes. However, random processing glitches would potentially have a more deleterious effect on the autocorrelation function, and for this reason, the power spectrum might be a more powerful tool than distributional statistics for characterizing HV data.

To this end, we constructed an experiment with the single purpose of collecting data that had extreme individual differences in RT variability. The task we chose was mental rotation, a standard tool in cognitive assessment, initially devised by Shepard (Shepard & Cooper, 1982) to clarify the nature of mental transformations. In our version of the task, a letter was presented at an angle of rotation of 0, 60, 120, 180, 240, or 300° on each trial. The letters were randomly drawn from a set of four (*R*, *Q*, *G*, and *F*), and on half of the trials the letter was mirror-reflected. The observer's task was to determine if the letter was mirror-reflected or not (pressing "1" on the keyboard if it was not and "2" if it was). Each observer completed a single block of 480 trials.

The typical data pattern generated in this task is a tent function with mean RTs that increase with angle up to 180° and then decrease with angle beyond 180°. The interpretation of this function is (a) that people mentally rotate the letter to its upright position in order to decide if it is mirror-reflected, (b) that it takes longer to rotate objects to more extreme angles (as if the objects actually existed in a euclidean space), and (c) that people rotate along the shorter available route (clockwise for angles greater than 180° and counterclockwise for angles less than 180°). The tent function is evident in the data described later in this article.

Selection of the subject population was guided by the use of a questionnaire constructed to elicit reports of the ADHD symptoms of inattentiveness, compulsivity, and distractibility. The items we were most interested in were typical of such assessments: "I am very energetic," "I tend to fidget," "I find it difficult to pay attention," and so forth. Initially, students attending psychology classes at the University of Texas were recruited, and they generally reported few ADHD symptoms. They also tended to generate low-variability (LV) data. This is not surprising, as florid ADHD symptoms do not enhance college performance. In order to find reliable sources of HV data, we decided to assess adults (primarily of young college age) in alcohol recovery (i.e., members of Alcoholics Anonymous, AA).

Alcohol abuse and ADHD go hand in hand. There are a number of ways in which they are associated:

- Response inhibition, one of the core constructs of ADHD (Arnsten, 2001; Barkley, 1997), is a predictor of problem drinking (Nigg et al., 2005).
- Sober alcoholics show cognitive impairments that are associated with ADHD (Tedstone & Coyle, 2004).
- People admitted to substance-abuse programs show high rates of ADHD symptoms (Hoegerman, Resnick, & Scholl, 1993).
- Most important, there are now concrete neurological hypotheses that connect ADHD and alcohol abuse. Hypofunction in the dopamine system of reward is implicated in both conditions (Smith, Molina, & Pelham, 2002; Solanto, 2002).

We make no claims here about the etiology of either disease, but it is manifestly the case that recovering alcoholics provide a large population for studying attention disorders. Indeed, almost all of our subjects who reported ADHD symptoms were drawn from the AA group.

Our final sample consisted of 15 undergraduates and 14 members of AA. Twenty-one of these people were of college age, and the remaining 8 were between 29 and 52. Subjects were rank-ordered in terms of their variability on the mental rotation task. The 9 with the lowest variability were retained as the LV group. The 9 with the highest variability were retained as the HV group. All 9 LV subjects turned out to be undergraduates, and none of them reported ADHD symptoms. Eight of the 9 HV subjects were attending AA meetings, and 1 was an undergraduate. The middle group was mixed, consisting of 5 undergraduates and 6 members of AA, who were found to be thoroughly shuffled when sorted on overall variability. The sort on variance thus extracted two relatively homogeneous extreme groups that were reliably coincident with reports of ADHD symptoms and certainly with life outcome.

In order to help readers appreciate just how different the HV and LV groups were, we show in Figure 2 the RT sequences from the subjects who were at the median in RT variance in these groups (5th ranked in each group of 9). Note that the scale in Figure 2 extends from 0 to 6 s, three times the range in Figure 1. Mental rotation is a more challenging task than deciding if two letters are the same or different, and it generates both slower and more variable RTs for comparable rates of accuracy. The graph

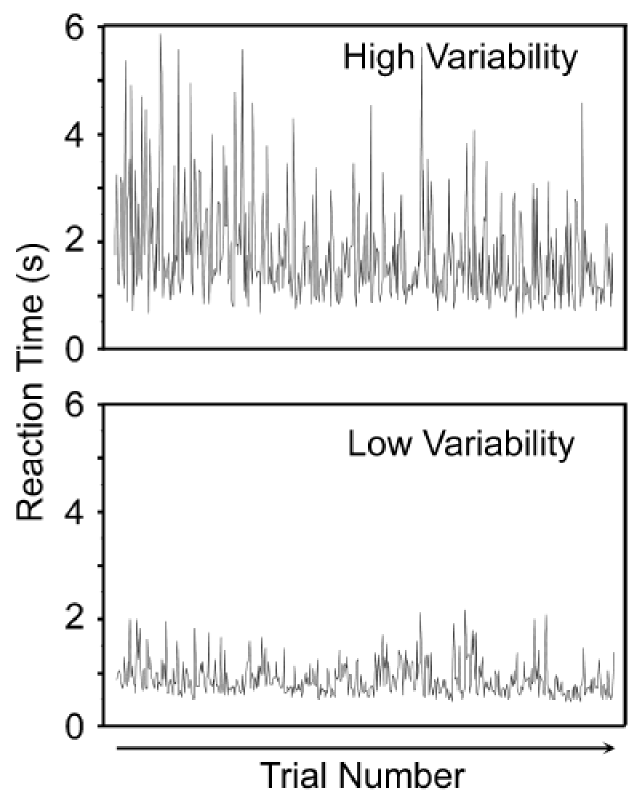


**Fig. 2.** Reaction time sequences from high- and low-variability observers in the mental rotation task. These sequences were taken from the 2 observers at the median variability for their respective groups.

for the HV observer in Figure 2 is filled with latencies in the range of 3 to 5 s, a very long time to decide if a letter is mirror-reflected. It might be difficult to credit the HV observer with a sincere effort, yet these data are representative of the group reporting ADHD symptoms and are quite similar to much of the data observed in the negative-priming studies conducted by Shin (2005). Moreover, all of our participants were willing and gave their time freely. There is no reason to regard this effort as insincere, and these data appear to be simply more evidence of the original observation by Castellanos and Tannock (2002)—that high variability in RT is typical in ADHD studies.[3]

## TWO PORTRAITS OF DATA VARIABILITY

We performed two kinds of analysis on the mental rotation data. In our first set of analyses, we extracted the mean RTs and determined the effect of angle, the main independent variable in mental rotation. We accomplished this in the usual way, by dicing the data up according to the angle of rotation, regardless of where the individual trials occurred in the sequence. Figure 3 shows the data picture that emerged from this analysis. This figure shows that both LV and HV observers mentally rotated the letters, as both groups produced tent functions. The principal difference between the two groups appears to be an RT offset of about 600 ms. The HV observers evidently consumed time in some activity that was independent of angle. This activity might have been task related (e.g., response mapping), or it could just as likely have been devoted to daydreaming, or whatever else might occupy roughly a second, on average.

There are two ways of interpreting these results. As both groups managed to do mental rotation, one might conclude that this task is not a particularly useful tool for understanding ADHD or, more generally, for learning what creates high data variability. Although there was a group-by-angle interaction, $F(5, 80) = 3.6$, $p < .005$, the slightly more peaked function produced by the HV group does little to invite interpretation. On the basis of these data, one could not claim that attention deficits change the rate of mental rotation, for example. Alternatively, one could focus on the 600-ms intercept shift in the HV data. From Figure 2, it is obvious that the entire HV data set is distinctly odd, and this is potentially a much more important fact than whatever the pattern of means might indicate.

Our second set of analyses treated the data not as a response to an experimental design, but as a temporal signal that was literally formed by the observers with each key press. RT latencies make wavelike patterns, and the power spectrum tells how the waves are nested. Prior to obtaining spectral estimates, we removed all treatment effects (angle, mirror-reflected or not), and so we effectively analyzed just the unexplained variation. The methods we used for computing the power spectra are described completely in a previous publication (Thornton & Gilden, 2005), which also addresses the various issues arising in spectral analysis, such as subject averaging, detrending of data, and window averaging. Our methods have been calibrated on large ensembles of both real and simulated data.

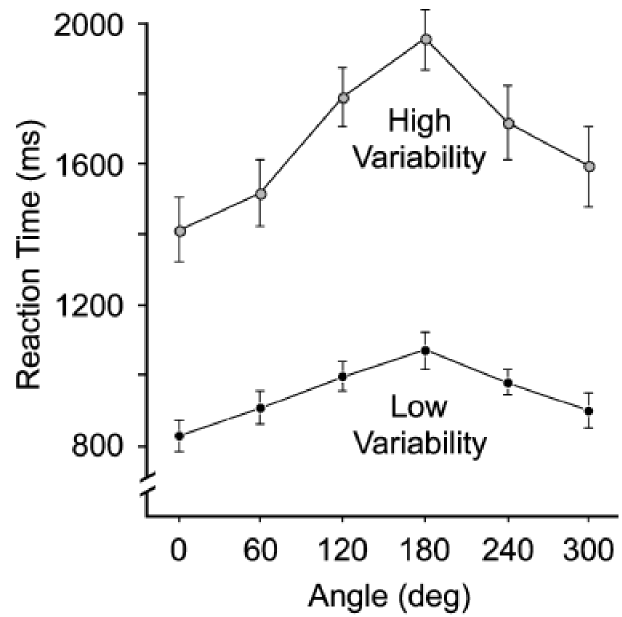


**Fig. 3.** Reaction time as a function of angle in the mental rotation task. Results are shown separately for the high- and low-variability groups. Error bars represent standard errors of the means.

Figure 4 shows the observer-averaged power spectra for both the LV and HV groups. The total spectral power for each group has been normalized to unity to facilitate a comparison of spectral shape. This transformation affects only the vertical offset in our log-log plot. The abscissa is frequency, indexed not by 1/seconds, as is usual in temporal records, but by 1/trial number. Thus, low frequencies refer to RT variation over widely separated trials, up to 256. High frequencies capture local RT variation spanning as few as 4 trials. In this figure, power refers to the squared amplitude of a sine or cosine wave in the RT time series at a particular frequency. It is clear from Figure 4 that the waves running through the RT data were of different amplitudes in the two groups; this implies that the two groups generated RT histories with different forms of autocorrelation. The LV power spectrum is quite similar to what is generically produced by normal adults in mental rotation and other choice RT tasks (Gilden, 1997, 2001). The HV spectrum does not resemble any published spectrum for RT sequences (Gilden, 1997, 2001; Van Orden et al., 2003, 2005; Wagenmakers, Farrell, & Ratcliff, 2004).

[3]It should be recognized that ADHD is not a well-defined diagnosis. There is no unique symptom or marker that indicates its presence. Indeed, it is not really clear what the disease label refers to. Our experience with adults diagnosed with ADHD (Shin, 2005) and our experience with AA attendees suggests that Castellanos and Tannock's (2002) comment about high variability is more than instructive; it defines a key signature of the attention-deficit disorders. Not only is high variability often produced by people with diagnosed ADHD, but high variability might be regarded as a principal diagnostic criterion of this disorder. Upon observing the HV data shown in Figure 2, one must wonder about its larger significance.

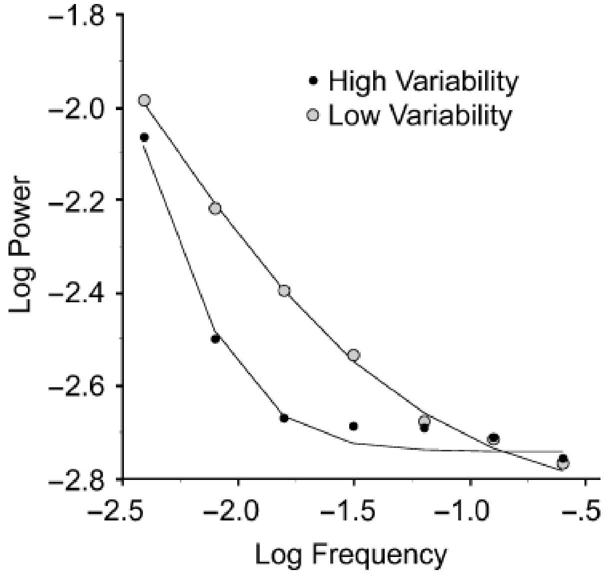


**Fig. 4.** Average power spectra of reaction time sequences for the high- and low-variability groups. The data are shown by circles. The lines represent theoretical fits to the two-source model described in the text.

Our concentration on the two groups with the least and most variability is a form of extreme-group analysis, a method that naturally generates uncertainty about the fate of the middle group and its lost impact on model specification (Preacher, MacCallum, Rucker, & Nicewander, 2005). In our particular application, the LV and HV groups do seem to map onto a meaningful taxonomic distinction (between normal attention and attention deficit), and the middle group did not in fact produce an intermediate kind of spectrum, as might be the case were spectra and variability related in a linear or even nonlinear fashion. Individual spectra from the middle group were divided between the two varieties shown in Figure 4; there was no discernible third variety. This result is consistent with benchmark calculations we performed on data from studies that involved only normal subjects. Dividing normal subjects into extreme groups based on variability did not produce two spectral classes. In order to observe unusual spectra, it is necessary to obtain unusual data, and although we use variability here as a measure of normality, we do not wish to imply that the underlying construct of attention deficit has continuous gradation.

To interpret the observed spectra, we fit a dual-source model that specifies how white and correlated noises are mixed together to produce the bowed spectra illustrated in Figure 4. A descriptive model that has provided good fits to RT data in our previous work (Gilden, 1997, 2001; Thornton & Gilden, 2005) is written as follows:

$$\mathrm{power}(f) = \frac{1}{f^{\alpha}} + \beta N(0,1),$$

where $f$ refers to frequency, $\alpha$ is the exponent of the fractal component, and $\beta$ is the amplitude of a white noise-source with unity variance and zero mean, $N(0, 1)$. The first and second terms in this equation are intended to model, respectively, the correlated and uncorrelated aspects of the RT time series. The lines in Figure 4 represent the best fits obtained with this model. These fits are meaningful in that the model does succeed in describing the observed spectral shapes ($\chi^2 = 0.0074$ for the LV group, $\chi^2 = 0.032$ for the HV group).

The model parameters proved to be informative. For LV spectra, the value of $\alpha$ was $-.88$, and the value of $\beta$ was 1.6. This means that the LV group generated an RT noise that was about 28%—$1/(1 + \beta^2)$—$1/f$ noise and about 72%—$\beta^2/(1 + \beta^2)$—white noise. Both the exponent and the percentages are typical for choice RT (Gilden, 1997, 2001). The HV parameters were quite different, with an $\alpha$ of $-2.1$ and $\beta$ of 3.5. This is an unusual finding, and its significance rests upon the fact that an exponent of $-2$ indicates a random walk. The large value of $\beta$ for this group means that the signal was mostly white noise, which accounted for 92% of the variance. The remaining 8% was accounted for by a process that might be thought of as RT diffusion. To put these results into perspective, one should compare the contribution of random-walk noise with the proportion of variance explained by the angle variable—the key manipulation in a mental rotation task. That letters were presented at different angles accounted for at most 4 or 5% of the total variance, and as little as 1% in the HV group. In this context, the 8% of the variance expressed in a random walk was not negligible. What was more negligible were the stimuli themselves.

## DISCUSSION

The spectral analysis of HV data suggests that the variability reflects more than the production of a few outliers. HV data sets have an entirely different correlational structure than LV data sets. This is an important point; HV data are not simply LV data with higher gain, as might be concluded from the display of mean trends. HV data contain a novel noise type, RT diffusion, that has not been reported in the cognitive literature. Unlike $1/f$ noise, diffusion has a straightforward meaning.

Random walks are created by a process that perseverates, that is, a process in which new states are built from their immediate predecessors. Formally, the random walk signal is generated by iterating

$$\text{new RT} = \text{old RT} + \text{random increment}.$$

As simple as this recursion relation is, it is nevertheless unexpected in human data. There is no theory or set of prior findings that suggests RTs would diffuse in this way. RTs are moderated by prior stimuli and by prior motoric response—this is what motor and stimulus priming are about—but RTs are not conceived to be moderated by other RTs. Note that the RT diffusion reported here should not be confused with the diffusion in models that use random walks to simulate information pickup. In such models, it is the growing evidence that diffuses, not the RTs themselves.

The picture that emerges from this experiment is as follows. There are some people who exhibit extremely high variability in RT. These people often report ADHD symptoms, and they often have life outcomes that include AA membership. The data these people generate in a mental rotation task look fairly normal insofar as the mean trends are concerned, although their RTs are slow. For this reason, one may assume that the usual stages of perceptual analysis, response selection, and response execution are active in their decision making. However, their RT correlations are not normal, and this is quite explicit when the RTs are viewed in terms of their trial history. More than 90% of the variance derives from an uncorrelated source of white noise, and the remainder is formed by a random walk.

The RT correlation function appears to be under the control of whatever it is that allows people to be vigilant. People who cannot maintain vigilance lose their place at some point in the normal processing chain. Loss of place results in the insertion of an off-task time interval into the RT. This interval, in the case of mental rotation, apparently may last upward of 5 s. The off-task time intervals are not entirely independent. There is a tendency for people to pause for as long as they have in the recent past, and this generates the observed random walk.

The principal difference, then, between data derived from people who can maintain vigilance and data from those who cannot is literally in the noise. It is not that one group produces noisy data and the other does not. In our methodology, any RT sequence would be mostly noise. The issue is the kind of noise that is present. Normal undergraduates produce copious amounts of 1/*f* noise as a natural consequence of decision making. People with attention deficits generate an erratic signal that develops from the intrinsic pressure of being asked to make a speeded response. This finding must serve as a caution to researchers who wish to use speeded judgment to test theories of attention dysfunction.

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