

Speculation about behavior, brain damage, and self-organization: The other way to herd a cat[☆]

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Accepted 2 December 2003

Available online 15 January 2004

Abstract

This article contrasts aphasic patients' performance of word naming and lexical decision with that of intact college-aged readers. We discuss this contrast within a framework of self-organization; word recognition by aphasic patients is destabilized relative to intact performance. Less stable performance shows itself as an increase in the dispersion of patients' response times compared to college students'. Dispersion is also more pronounced for low-frequency words than for high frequency words. We speculate, that increased dispersion originates in a reduction of constraints that support naming and lexical decision performances. A sufficient reduction of constraints yields qualitative changes in performance such as the production of semantic errors in deep dyslexia. These hypotheses are offered as alternatives to postulating distinct modules.

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1. Introduction

Behavior comprises the effects of specialized brain components—specialized mechanisms of perception, language, motor control, and so on (plus random background noise). Thus behavior may be reduced to the causal properties of the specialized components. Cognitive neuropsychology originates in these intuitive assumptions. They promote equating causes with brain damage and effects with behavior, as though behavior is transparent to causal modules in the brain. Consider the case of deep dyslexia. Deep dyslexia is largely defined by the semantic error, as when BUSH is mistakenly read aloud as /tree/. Semantic errors have suggested to theorists that one, or more than one, component of the brain's reading mechanism is partly or completely damaged (e.g., see Buchanan, Hildebrandt, & MacKinnon,

1999, or Morton & Patterson, 1980; Plaut & Shallice, 1993, respectively). In other words, the qualitative departure from intact behavior (the effect) originates in damage to a specific isolable component or components of the brain (the cause). However, there are many natural systems for which this kind of cause and effect reductionism is not possible. We claim that human beings are in the latter category.

2. Self-organization

Some natural systems, perhaps all living systems, self-organize their behavior at 'the boundary between order and chaos' (Depew & Weber, 1995). Self-organization yields emergent behavior. But if human behavior is emergent, then we would necessarily re-examine the cause and effect reductionism that is the foundation of modern cognitive neuropsychology. We would be forced to re-think cognitive neuropsychology—how behavior relates to the mind and body, how we should study behavior, how behavior relates to brain damage, and so on. Such a fundamental change requires first that the

[☆] We thank H. Baayen for insightful comments on an earlier version of this paper and Craig Harwood for assistance with stimulus set construction. This research was funded through the SSHRC MCRI program.

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conventional research program is found lacking and second that the new research program can be strongly motivated. Although it remains a contentious claim, one can currently make a case that these conditions for change do exist.

Painstaking self-examination within cognitive neuropsychology, and elsewhere in cognitive science, has called into question the primary methods of neuropsychology, the conceptual and methodological tools of the trade. The methods of dissociation and double dissociation are theory dependent (Shallice, 1988). Dissociations have a circular reliance upon the *a priori* truth of modularity. They cannot supply independent evidence for or against their parent modular theory. Double dissociations do not imply distinct modules, for example, unless it is true before the fact that the modules exist. One must have a correct roadmap of cognitive modules before the fact to reliably interpret dissociations after the fact.

Modularity itself is not supported by a reliable basis in evidence (Farah, 1994; Fodor, 2000; Uttal, 2001). In light of these facts, Shallice (1988) has suggested that cognitive neuropsychologists rely on expert intuition concerning deficits and modules, but no broad based agreement can be reached on whose intuitions to trust (compare Watkins, 1990). Particular accounts of patient data decide which deficits are meaningful, but also which are not, so competition among accounts tends toward stalemate (Van Orden, Pennington, & Stone, 2001).

The positive case for self-organization and emergence is more hopeful. Measurements of intact human performance reveal signatures of self-organization (Kelso, 1995). One ubiquitous signature appears in the background noise of measurements of behavior. Background noise is the irregular pattern of variation across repeated measurements of human performance. It is what remains after we minimize or eliminate effects of task, experimental manipulations, and other *external* sources of variability in behavioral measurements. Conventional analyses assume that background noise is unstructured random noise, but instead we find a pattern called 1/f noise, or pink noise, a coherent nested pattern of correlated variability across trials, an informative so-called fractal pattern in time.

Background noise, as pink noise, is expected if a system self-organizes its behavior (Bak, 1996; Jensen, 1998). Background noise refers to *internal* sources of variability. It tells us about the intrinsic dynamics of mind and body, how processes of mind and body interact. Ubiquitous pink background noise suggests processes of mind and body that change each other's dynamics in their interaction. This kind of dynamics is called *interaction-dominant dynamics* (Jensen, 1998). Processes do not simply interact; they change each other through their interaction.

It is especially pertinent to our purpose that pink noise has been found in response time data. The many

kinds of response time experiments range from simple reaction time, through the purportedly *automatic* task of word naming (Van Orden, Holden, & Turvey, 2003a; Van Orden, Moreno, & Holden, 2003b), to tasks that require *cognitive control* such as response time for mental rotation or lexical decision (Gilden, 1997, 2001). The presence of this pink noise signature means that we may seriously consider a self-organization hypothesis. Like many other natural systems, both intact and brain damaged participants behave as self-organizing entities.

3. Stability of performance options

How does a cognitive system behave at the boundary between order and chaos? Mind and body together produce behavior; their processes never work in isolation. As noted, self-organization implies processes that change each other's dynamics as they interact. Consequently, within limits, interdependence allows changes in any one part of the system to be reflected throughout the entire system. Human behavior is something like an irreducible creative stream. One implication is that component "effects" cannot be sorted out of such interdependent dynamics. Consequently, within the new research program, the interactions themselves become the salient objects of study, not necessarily the interacting components (Van Orden et al., 2003a).

In brain damage, large or small changes in the local interactions of the nervous system may result in catastrophic qualitative changes at the level of global behavior. Likewise in self-organizing systems, small changes in the local interaction among processes can be amplified to become qualitative changes in global behavior. To illustrate this possibility, Farrar and Van Orden (2001) and Kello (2003) mimicked dissociations and double dissociations using small changes in parameters of self-organizing "neural" networks. In Kello's model, tiny changes in a single parameter sufficed to mimic the regularization error (PINT pronounced to rhyme with /mint/) as well as "absent" pseudoword naming (words are named correctly; pseudowords are not)—a double dissociation. In Farrar and Van Orden, tiny changes in two model parameters sufficed to mimic the previous double dissociation plus the semantic error of deep dyslexia (BUSH named as /tree/, mentioned at the beginning of this article), as well as a dissociation in picture naming of spoken vs. written responses (the spoken response to a picture of a bush is /tree/, but the written response is BUSH). These neural-network existence-proofs demonstrate why qualitative changes in behavior need not imply functional distinctions in the brain. In light of the evidence for self-organization, qualitative changes cannot be taken at face value to distinguish components of mind or brain (Van Orden, Jansen op de Haar, & Bosman, 1997; Van Orden et al., 2001).

The standard assumptions regarding patient data, and indeed regarding unimpaired performance, may be incorrect. But does that mean that patient studies are futile? Of course not. It simply changes the way in which we think about patient data. In particular, our focus changes from behavioral “effects” to the stability of performance options. For instance, Farrar and Van Orden’s (2001) network simulations mimic dissociations because tiny changes in the model’s parameters change the relative stability of the model’s response options. Relatively stable interactions among nodes are the source of the model’s correct pronunciations and relatively fast pronunciation times. However, after tiny changes in parameters, correct and incorrect pronunciations exchange stability. What was previously the more stable correct pronunciation becomes less stable and is no longer expressed. Although the previously less stable error pronunciation does not gain stability, in an absolute sense, it becomes relatively more stable than the correct pronunciation and now shows itself as a pronunciation error. Notice the resemblance to the conventional notion of “release from inhibition.”

Performance stability is estimated by performance variability. Speaking very loosely, we shift our attention from performance averages to performance variances, estimates of dispersion of response times. We are not the first to note that impaired performance shows increased variability relative to intact. For example, college students’ response times pile up in a more narrowly dispersed distribution compared to elderly participant data and patient data (in some tasks, compare Anderson, Mennemeire, & Chatterjee, 2003; Hulstsch, MacDonald, & Dixon, 2002; Shammi, Bosman, & Stuss, 1998; Stuss, Pogue, Buckle, & Bondar, 1994). Less stable performances include a wider dispersion of response times mostly exaggerated in the direction of slow response times. This increasingly familiar observation of variability in patient data fits well within the self-organization hypothesis. We describe this fit with respect to contrasts of variability found in naming and lexical decision data from patients and from college-aged participants. Though we will have more to say about response times it may also help to think of errors in terms of stability.

For instance, most college students produce the same kinds of responses—correct responses—on almost all trials of most experiments. This is certainly true of word naming when the items to be named are common monosyllabic words. Patients who have suffered brain damage produce a more varied mix of correct and incorrect responses under the same conditions, both across trials and across participants. Such errors are response options that we claim are implicit in intact performance. Errors are potentialities of intact performance that are realized by brain damage. In a sense then, errors may reveal hidden degrees of freedom,

potential options that usually remain hidden in correct performances (Farrar & Van Orden, 2001). Consequently patient data may reveal constraints that are not easily seen in intact performance.

An analogy can be made to the connection weights in neural-network models. Connection weights reflect previous co-occurrences of node-activity. For example, relations (“connections”) between words’ printed and spoken forms (“nodes”), and their pattern of use, their semantics, constrain the pronunciations of deep dyslexics. Constraints that have accrued from relations between word form and function limit the possibilities for pronunciation. Previously less visible form-semantic constraints are revealed in the semantic errors. This means, in effect, that semantic errors are latent in correct pronunciations, although form-semantic constraints may be elicited in precise contexts of laboratory experiments. For instance, form-semantic relations, like relations between spellings and pronunciations, have been teased out of intact performance (Farrar, Van Orden, & Hamouz, 2001; Pecher, 2001; Pexman & Lupker, 1999; Pexman, Lupker, & Hino, 2002; Strain, Patterson, & Seidenberg, 1995).

Constraints are limits of possibility; limits on the set of potentialities that a system may express. Consider a somewhat silly example. Suppose you have the goal to move your cat into a cat carrier. A Newtonian solution would be to kick the cat in the direction of the carrier’s opening. One makes of oneself a cause and the effect is a cat on a trajectory that leads into the carrier. A more humane way to achieve the same goal would be a bubble fence of sorts, a flexible bubble of plastic that surrounds the cat and the cat carrier. The bubble constrains the movements of the cat; the cat cannot get outside the bubble. Now shrink the volume of the bubble toward the opening of the carrier. As the bubble shrinks, the cat’s freedom to move is more and more constrained. Eventually the only remaining degree of freedom is through the opening of the carrier.

Traditional cognitive neuropsychology stems from the Newtonian metaphor of cause and effect, representations cause action. Conventional research dissociates internal causes (representations) from other representations and from external contexts of action. Control follows a causal chain of representations between stimulus and response or between intention and action (Van Orden & Holden, 2002). On the other hand, self-organization relies on the metaphor of constraint. A hierarchy of interdependent constraints, at multiple scales of time and space, limit the possibilities for behavior. External and internal constraints are understood in terms of the same theoretical language. Narrow constraints come into and out of existence on the time scales of the changing situations in which action occurs. Control is an emergent property a product of the interaction between organism and environment (Van Orden et al., 2003a, 2003b).

4. Performance after brain damage

Constraints, stability, and variability could prove to be useful concepts to understand the consequences of brain damage. The present study compares word-naming accuracy and lexical-decision performance in correlation analyses. These two reading tasks, *word naming* and *lexical decision*, are the most commonly used laboratory reading tasks. As we will describe, the pattern of inter-correlation among their performance measures is notably different for patients than for intact participants. Our goal here is simply to describe differences between patients and intact participants in terms that take into account self-organization. We did not conduct a definitive study. Experiments that motivate self-organization require very large data sets and specialized tools of analysis. Our goal is to frame familiar kinds of data in the language of self-organization. We attempt to make modest speculative headway toward re-thinking the consequences of brain damage.

4.1. Methods

4.1.1. Participants

Participants included 45 undergraduate students and nine language impaired patients. Eight of the nine patients had language deficits subsequent to stroke while the ninth patient had language deficits that arose from treatment of a brain tumor. All patients were right handed and all had left-hemisphere damage, regardless of cause.

The college students volunteered for course credit; the patients were paid 10 dollars per hour. One student's data were dropped from the analysis secondary to a data entry error. All remaining students and patients performed both word naming and lexical decision.

4.1.2. Procedure for the word naming tasks

College students read aloud 25, rare, multisyllabic, English words printed in black 16-point Arial font on a white sheet of paper. These 25 words presented moder-

ate to high levels of pronunciation difficulty. College level readers would perform at ceiling for naming of monosyllabic words (like those used with the patients). We required words of sufficient pronunciation difficulty to pull performance down from ceiling. These targets were initially gathered from lists of words from college aptitude tests. From these lists, 285 items were randomly selected. Each item was subsequently read aloud by a 12-year-old volunteer and item selection was based on his ease of pronunciation for each word. The final list included 13 words that were pronounced correctly on the first attempt (e.g., *mendacious*, *veracity*, and *maladroit*) and 12 words that were incorrectly pronounced or pronounced with difficulty (e.g., *beatify*, *apocryphal*, and *oligarchy*).

Patients read aloud 300 common monosyllabic English words printed on index cards in 18-point Arial font (see Buchanan, Hildebrandt, & MacKinnon, 1994 for items). Both naming tasks were participant paced; no time limits were imposed.

4.2. Procedure for the lexical decision task

The procedure for the lexical decision task was the same for both college students and patients. The lexical decision targets comprised 148 pronounceable nonwords and 148 words. The words were 74 yoked-pairs of single-syllable high- and low-frequency targets. Each yoked pair was similar in spelling and pronunciation and matched precisely for number of letters and first phoneme. In each lexical decision trial, the target letter-string was preceded by a 250-ms fixation-cross and then presented individually on a computer screen using DirectRT software (Jarvis, 2002). The target remained on the screen until the participant pressed either a *word* or *nonword* response key. Word and nonword trials were presented in the same fixed randomized order for each participant. Participants were instructed to respond quickly without compromising accuracy.

Table 1

Correlation profile across naming and lexical decision performances by nine patient participants

	RB	MD	WM	BV	JM	JO	MH	LA	BC	<i>r</i> with <i>d</i> -prime	<i>r</i> with word naming accuracy
<i>p</i> -Prime	1.3	2.2	2.3	2.6	2.6	2.8	3	3.5	3.7		.36
<i>SD</i> all words	1583	1831	610	958	853	1017	813	523	343	-.77*	-.56**
<i>SD</i> low-frequency words	1248	2175	776	936	1320	1330	2175	531	357	-.65*	-.70*
<i>SD</i> high-frequency words	1822	1501	429	748	502	464	1501	357	282	-.80*	-.31
Word naming accuracy	79%	35%	68%	50%	79%	23%	97%	100%	95%	.36	

* $p < .05$.

**Marginal reliability ($p = .06$).

4.3. Results

4.3.1. Word naming results

College students and patients produced wide ranges of accuracy scores (College students: range = 8–80%, mean absolute score = 11 correct pronunciations out of 25, $SD = 4.67$; patients: range = 23–99%, individual Patients' accuracy scores can be found in Table 1). A detailed description of patients' errors is beyond the scope of the present paper, but two of the patients (JO and BV) produced the semantic errors characteristic of deep dyslexia and the predominate type of error overall was omissions, followed by words that were similar in orthography or phonology to the target word. College students produced no semantic errors, omissions, or word substitutions. College students made errors of mispronunciation that are common to these rare words /beat-if-eye/ rather than /be-at-if-eye/ and /ap-o-cry-ful/ rather than /apo-cra-ful/, for example.

College students' and patients' errors are different in kind, but they both express constraints that are latent in correct pronunciations. Patients' errors replace otherwise familiar words' pronunciations. Correct pronunciations have exchanged stability with error pronunciations that would be highly unlikely in intact performance—bizarre semantic errors for instance. As we already explained, these errors reveal response options that are latent in intact performance to the same words.

Students' errors are so-called regularization errors. Rare words are given novel but not entirely unexpected pronunciations. These error pronunciations reveal constraints that are inherited from other words similar in spelling and pronunciation—general statistical patterns of relations between spelling and pronunciation (cf. Kessler & Treiman, 2001).

If the rare words of our study became familiar words for the same college students, then the regularization errors would become latent in their performance. A correct pronunciation in this case requires acquisition of word-specific constraints, a correct pronunciation option with greater stability than the regularization error option.

All these possibilities have been demonstrated as existence proofs. That is, neural-networks acquire constraints as their connection weights change, including general statistical constraints that can produce regularization errors and word-specific constraints that correct regularization errors. Also, simulated brain damage can change the configuration of constraints in a neural-network model to reveal latent response options as pronunciation errors (e.g., Plaut, McClelland, Seidenberg, & Patterson, 1996).

4.3.2. Lexical decision accuracy measures

We calculated the *d-prime* statistic for performance in the lexical decision task, to be used in the analysis of

correlations with other statistics. *d-Prime* is a bias-free estimate of sensitivity to the *word/nonword* distinction. It takes into account both correct and incorrect responses. A high *d-prime* score means that the participant readily distinguishes words from nonwords. *d-Prime* is computed using the *false alarm* rate (proportion of incorrect *word* responses to nonwords) and the *hit* rate (proportion of correct *word* responses to words). Both college students and patients produced relatively wide ranges of *d-prime* scores (College students: range = 2.0–5.1; patients: range = 1.3–3.7, individual Patients' scores can be found in Table 1; the patients' lexical decision data were reported previously in Moreno, Buchanan, & Van Orden, 2002.)

We collapsed across the frequency distinction to calculate *d-prime*. The *d-prime* calculation requires a hit rate less than 100%. This rarely occurs for high frequency words; most participants get 100% correct. We used accuracy instead of *d-prime* to evaluate the frequency manipulation (see the section below concerning word frequency).

4.3.3. Contrast of response time dispersion between patients and intact participants

We expected that dispersion of response times would distinguish between patients and college students. We tested this expectation in a nonparametric variance ratio test that is related to a standard ANOVA. First we computed the variance for each patient's and each college student's distribution of correct response times that fell between 200 and 2500 ms. We summed the variances within each group, and divided each by $n - 1$; $n - 1$ equals 8 for the patients and 43 for the students. The result is a variance statistic that is an analogue to the mean square in an ANOVA. Dividing the two variance statistics yields an *F* ratio, $F(8, 43) = 2.32$.

At this point, if a true *F* statistic had been computed, and we were confident that the sampled population (or populations) followed a normal distribution, then we could use a standard *F* table to determine statistical significance. However, our statistical question does not plug directly into the logic of an ANOVA, and the normality assumption seems tenuous at best. Furthermore, there were far fewer patients in our study than college students, and it is possible that the obtained result is a consequence of that fact. A nonparametric bootstrap procedure addresses these concerns (Efron & Tibshirani, 1998).

The bootstrapping procedure evaluates the likelihood of obtaining the previous observed *F* value by chance alone. The logic of the nonparametric bootstrap test is straightforward. We mix together the nine patients' and the 44 college students' variance statistics to create a distribution of 53 values reflecting the null hypothesis—namely, that patient and student variance estimates come from the same population. If the null hypothesis is

true, then all permutations of the patient–student mixtures are, in a sense, equally likely.

The bootstrap procedure repeatedly re-samples, with replacement, all 53 variances. With each replication an F ratio is computed just as it was for the observed F ratio, dividing the variance of 9 samples by the variance of 44 additional samples. Actual patient variances and student variances could end up in either grouping. To estimate statistical reliability, we divided the number of times the bootstrap F value equaled or exceeded the previous observed F value (2.32) by the total number of bootstrap replications. This yields a very good estimate of the chance probability of an F ratio equal to or greater than the observed F ratio. We ran this analysis several times, first using 1000 and then 10,000 bootstrap replications, and always obtained probability estimates that fell well below .01, a statistically reliable difference. Thus patients' variance statistics are reliably larger than students' variance statistics; patients' response times are more widely dispersed than students' in the direction of exaggerated slow times.

We next used the bootstrap procedure to compare variance statistics for response times to high and low-frequency words taken separately. The observed F for patients' vs. students' response times to high frequency words was 1.61; the p value hovered between about .06 and .04 across repeated bootstrap analyses, a marginally reliable outcome. The observed F for the contrast between patients' vs. students' response times to low frequency words was 2.33, which is $p < .01$ by the bootstrap. Patients produce reliably more-variable response times to low-frequency words than do students.

Let us sum up the results of the bootstrap analyses. Patients' response times are more widely dispersed in the direction of exaggerated slow response times. However, this difference is only clearly reliable in response times to low-frequency words.

4.3.4. Lexical decision results (word frequency)

Both college students and patients produced traditional word-frequency effects that are seen using standard inferential statistics (College Students' Accuracy: $M_{\text{HIGH}} = 97\%$, $M_{\text{LOW}} = 86\%$, $t(43) = 9.99$; RTs: $M_{\text{HIGH}} = 709$, $M_{\text{LOW}} = 824$, $t(43) = 11.76$; Patients' Accuracy: $M_{\text{HIGH}} = 95\%$, $M_{\text{LOW}} = 81\%$, $t(8) = 6.58$; RTs: $M_{\text{HIGH}} = 1558$, $M_{\text{LOW}} = 1894$, $t(8) = 29.17$). The traditional exclusive focus on means dovetails with the widely trusted assumption that word-frequency modulates the availability or "force" of a lexical representation—the cause of a word response. It is usually misleading, however, to use means, exclusively, in response time analyses (Andrews & Heathcote, 2001; Balota & Spieler, 1999; Plourde & Besner, 1997).

RTs to low-frequency words are reliably more variable than to high frequency words (College Students: $SD_{\text{HIGH}} = 254$, $SD_{\text{LOW}} = 322$, nonparametric sign test

$z(44) = 3.36$; Patients: $SD_{\text{HIGH}} = 749$, $SD_{\text{LOW}} = 1065$, nonparametric sign test $z(9) = 2.0$). Moreover, the magnitude of a participant's word-frequency effect is reliably predicted by the same participant's magnitude of difference in response time variability between low and high frequency words ($SD_{\text{LOW}} - SD_{\text{HIGH}}$). This was true for both college students and patients ($r = .73$ and $r = .89$, respectively).

The relation between the relative size of traditional word-frequency effects and the relative dispersion of RTs is nested within the contrast between patients' and students' performance. Patient's distributions of correct response times are more widely dispersed than student's distributions, and the exaggerated variability that distinguishes less stable patient performance from more stable student performance is, in a sense, echoed along the continuum of within-participant variability. Relatively high performing students or patients display less overall variability than their low performing peers, and high performers also show less discrepancy in variability between low and high frequency words.

The relation between relative dispersion and relative mean RT has previously been examined from the conventional reductive perspective. A reductive analysis seeks to partition effects among the parameters of distributions or between separate distributions entirely. The most common practice has been to parse effects among the parameters of Gaussian vs. exponential distributions, where the distributions themselves are summed (convolved) to mimic the overall dispersion of participant RTs. These attempts have not been successful. Over the course of four decades, such attempts have failed time and again to reliably parse word factors among distribution parameters (Moreno, 2002). This leaves the door open to alternative approaches such as our own.

In fact, Moreno (2002) simulated frequency effects as largely due to more variable (less stable) word responses to low-frequency words. These assumptions motivated his simulations: the word and nonword responses of lexical decision are the response options (attractors) of a nonlinear dynamics system. Lexical factors translate into constraints that yield more or less stable word response attractors. The factor word "frequency" estimates the word's normative probability of occurrence in broadly sampled text, which estimates opportunities to acquire word-specific constraints. But every person has an idiosyncratic history with every word, which has different implications for high and low-frequency words.

A relatively high frequency word is likely to recur often in many topics of discourse. High frequency words are likely to be high frequency for all readers regardless of idiosyncrasies of interest or background. Consequently, the degree of constraint on word responding is more uniform for high frequency words, which yields less dispersed distributions of word response times.

The typically low rates of occurrence for low-frequency words mean that they are less likely to appear in broadly sampled text, but participants sample text narrowly to suit their interests and backgrounds. There are no guarantees that a low-frequency word for the experimenter is a low-frequency word for the participant. The variety of participants' samples of text yields more variable patterns of word recurrence, which yield less stable *word* responses overall, more widely variable constraints equal more widely dispersed performance measures (Holden, 2002; Van Orden et al., 2003b).

In summary, cognitive constraints intertwine with other embodied constraints to self-organize a *word* response, whether a key press or the spoken word 'yes.' A reader is less likely to accrue constraints to words that recur less often in print. Thus *word* responses to low-frequency words may self-organize with respect to weaker constraints, which implies slower and more error prone performance (Grossberg & Stone, 1986). We have framed the distinction between high and low-frequency words in terms of the relative likelihood of recurring opportunities to accrue constraints. We claim that the traditional view of word frequency as modulating a cause, or as a factor that produces an effect, has obscured the actual stochastic nature of word frequencies and the attendant implications for performance such as stochastic changes in relative dispersion.

4.3.5. Correlations between word naming and lexical decision

We previously claimed that brain damage weakens or eliminates accrued constraints that had previously served intact performance. The conceptual framework is sensibly applied to understand between-participant differences in performance variability (patient vs. students) as well as within-participant between-word differences (word frequency). The focus on abstract stochastic constraints and stability creates common ground for word factors and brain injury. In this section we contrast patient and student performance again using correlation analyses that compare performances of the two tasks.

Table 2
Correlation profile across naming and lexical decision performances by intact participants

	Averaged values across 44 participants	<i>r</i> with <i>d</i> -prime	<i>r</i> with word naming accuracy
<i>d</i> -Prime	3.08		.54*
<i>SD</i> all words	300	.21	.05
<i>SD</i> low-frequency words	322	.18	.20
<i>SD</i> high-frequency words	254	.22	.04
Word naming accuracy	46%	.54*	

* $p < .05$, one-tailed test.

Table 1 summarizes the analyses of correlations in patients' data, and Table 2 does the same with college students' data. In Table 2, word naming accuracy and lexical decision *d*-prime are reliably correlated, but nothing else. In Table 1 most of the measures of dispersion are reliably correlated with word naming and *d*-prime, but the previous correlation between accuracy scores is not statistically reliable. The pattern of inter-correlation in Table 1 is almost exactly opposite to the pattern of Table 2. The two patterns together resemble a double dissociation—a double dissociation of patterns of inter-correlation among accuracy and dispersion measures, one could say.

The outcome for college students portrayed in Table 2 makes sense. College students were asked to name aloud extremely uncommon words. Aptitude for articulating the pronunciation of an uncommon word is likely related to identification of more or less common words in lexical decision. In a conventional account, one might even propose that an association between task performances implies one (or more) shared modules, a module that recodes printed words into phonologic representations for example. However, a more conservative possibility, more in line with the present story, would be a common source of constraints that promotes accuracy in both of the tasks—say time spent reading. This possibility is more scientifically conservative because it need not bring into existence a shared causal entity.

The picture of patients' performance that Table 1 presents is pretty much the opposite of Table 2. The association we observed in college students' performance is not reliable in patient performance. Also, whereas college students produced no reliable correlations with RT dispersion, patients' dispersion measures are all negatively correlated with accuracy and most of these correlations are statistically reliable. A conventional approach might suggest that the common component of word naming and lexical decision has been partly or wholly eliminated by brain damage, and the damage reveals new associations between dispersion and accuracy.

We pointed out previously that word-specific constraints accrue stochastically; they depend on a reader's idiosyncratic history. Constraints also disappear stochastically. Their specific vulnerabilities to brain damage cannot be known a priori. That is why it would be impossible to predict exactly the word-errors that any particular patient would produce.

Brain damage causes stochastic changes in the matrix of constraints. Thus accuracy scores in naming vs. lexical decision would be perturbed by two relatively independent sources of random variation, because we chose different words for naming than for lexical decision. As a consequence, patients' word naming and lexical decision accuracy are not reliably correlated.

Nevertheless, patients' measures of RT dispersion predict accuracy; increased dispersion is associated with less accurate word naming and lower *d*-prime scores in lexical decision. In particular, the patients' *SDs* for lexical decision times to low-frequency words reliably predicts overall word-naming accuracy (compared to *SDs* to high-frequency words for instance).

Low-frequency words as a class usually recur infrequently. Low-frequency words accrue constraints infrequently and are more vulnerable to perturbation by an insult to brain integrity (compare Grossberg & Stone, 1986; Plaut et al., 1996). With respect to brain damage, low-frequency words compare to high-frequency words like canaries to coal miners. All other things equal, they are the first to go. Word naming is similarly vulnerable. The two canaries are not conjoined twins; they simply share the same cage, as we explain next.

Performance of word naming requires completely articulated constraints to produce a singular articulation of each word. Constraints must coordinate pronunciations across a state space with many degrees of freedom. Lexical decisions, by contrast, appear to collapse all constraints from all sources redundantly onto a single dimension of lexicality (Estes & Maddox, 2002). Reliance on a less redundant matrix of constraint leaves word naming more vulnerable. All other things equal, word-naming performance is more vulnerable to perturbation than lexical decision. Dispersion of low-frequency-word lexical-decision RTs is correlated with overall word naming accuracy by their coincident vulnerability—their shared cage.

The flip side of the previous situations shows itself in the strong negative correlation between patients' *SDs* for lexical decision times to high-frequency words and the *d*-prime statistic. The constraints corresponding to high-frequency words are most likely to be preserved after brain damage; they are the last to go. Thus wide dispersion of high-frequency word response-times is a good indication that constraints overall have been decimated. For instance, damage that so fully perturbs lexical decisions pushes word naming to the floor, thus the lack of a statistically reliable correlation. Widely dispersed RTs to high-frequency words are the last gasp of lexical decision, so to speak. Sensitivity to the word/nonword distinction shrinks as the distribution of high-frequency word RTs expands.

5. Discussion

We set out to discuss ordinary patient data in terms that are agreeable to a self-organization hypothesis. Our purpose was simply to demonstrate that patient data remain an important source of knowledge about system dynamics, were we to take a self-organizational approach. We also described a stochastic view of word

frequency that takes into account idiosyncratic word recurrence across a reader's lifetime.

A self-organization approach may also supply conceptual tools more in line with the phenomena of cognitive neuropsychology. The striking consequences of brain damage for a science of neuropsychology are unpredictable qualitative changes in behavior. For instance, qualitative developmental changes occur that qualify how or whether extent of damage predicts behavioral changes (Lea, 2001). Moreover lesion size is not a good predictor of severity of behavioral changes (e.g., in adult aphasics Fredriksson et al., 2002). The character and severity of deficits are not adequately predicted by the quantity of change in a brain (as they would be in a straightforwardly linear system).

Qualitative changes have been the center of discussion since a recognizable neuropsychology came into existence (Shallice, 1988). Before brain damage, a person says /bush/ when shown the word BUSH, after damage the same person says /tree/. Abrupt qualitative change is also the defining feature of strongly nonlinear behavior. Abrupt qualitative changes, the bread and butter of cognitive neuropsychology, are the defining facts of nonlinear dynamical systems.

Self-organizing systems are themselves strongly nonlinear, and we note again that evidence exists for the self-organization hypothesis. Many cognitive scientists concede some version of these facts—who still doubts that the mind, brain, and body entail strong nonlinearities? Our goal in this article has been to move further toward an understanding of what that could possibly mean.

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