

## **A Proper Metaphysics for Cognitive Performance**

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*The general failure to individuate component causes in cognitive performance suggests the need for an alternative metaphysics. The metaphysics of control hierarchy theory accommodates the fact of self-organization in nature and the possibility that intentional actions are self-organized. One key assumption is that interactions among processes dominate their intrinsic dynamics. Scaling relations in response time variability motivate this assumption in cognitive performance.*

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**KEY WORDS:** intentionality; control hierarchy theory; self-organized criticality; 1/f scaling.

Conventional research efforts in cognitive psychology trust Aristotle's maxim that nothing can cause or move itself (Gibbs & Van Orden, 2001). The entailed metaphysics excludes intentional behavior, as when laboratory participants voluntarily perform cognitive tasks (Juarrero, 1999). Response time is the most common measure of cognitive performance, and new response time studies corroborate phenomena consistent with self-organized criticality—a capacity for self-control. We illustrate these phenomena with pronunciation times from speeded word naming. To see these data as confirmatory, however, requires a metaphysics that acknowledges self-organized behavior in cognitive performance. This is the metaphysics of control hierarchy theory which we contrast with conventional structural hierarchy theory.

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## STRUCTURAL HIERARCHY THEORY

Most research efforts in cognitive psychology concern state dynamics of the mind—the series of mental representations that result in behavior (Markman & Dietrich, 2000). Structural hierarchy theory distinguishes states of the mind from the rest of nature, insofar as nature is a nearly decomposable system (Simon, 1973). Nearly decomposable systems comprise a hierarchy of structures nested one inside the other like Chinese boxes that are vertically separated in time. *Vertical separation* means that *larger* boxes change states on *longer* time-scales. For example, some scientists believe linguistic competence changes on the *very long* time-scale of evolution, whereas reading and writing refer to the *long* time-scale of cultural change. Thus language and culture, on their longer time-scales, present a static background for states of mind in a laboratory trial of word naming.

Vertical separation in time relegates each system to its own causal scale. Causal segregation treats each as a separate flowchart of component causes. This metaphor extends the metaphysics of efficient causes to cognitive systems. A flowchart of causal states for word naming begins with stimulus-input, a *printed word*, and ends with response-output, a *pronunciation*, and, in between, comprises a chain of mediating representations.

Mediating components interact additively, an assumption Simon (1973) dubbed *loose horizontal coupling*—an example of the superposition principle. For instance, the additive factors method is a test for loose horizontal coupling (Sternberg, 1969). Experiments with several experimental manipulations in factorial designs provide the opportunity for interaction. If the interaction of two or more factors is strictly additive, then the manipulations satisfy the superposition principle. They selectively influence distinct components. But nonadditive interaction effects are the rule in cognitive experiments, and a vast nexus of interactions across published experiments precludes assigning any factors to distinct components (Van Orden, Pennington, & Stone, 2001). Moreover, cognitive effects are conditioned by task demands, culture, and language. Consider the implications within the guidelines of additive factors logic. Cognitive factors are neither individuated as causes, nor causally segregated from the context of their manipulation—task, culture, or language.

## CONTROL HIERARCHY THEORY

Control hierarchy theory plays a fundamental role in nonlinear analysis, like that of structural hierarchy theory in linear analysis. A control

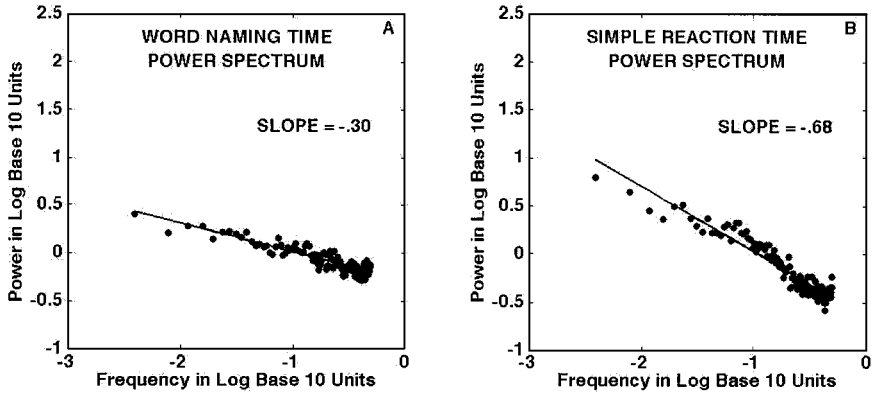
hierarchy is a hierarchy of dynamic structures vertically coupled in time. Positive feedback between different scales is the basis of vertical coupling and self-organization (Pattee, 1973). *Vertical coupling* implies that embodied cognitive constraints directly modulate motor coordinations. Interactions between vertically coupled processes dominate their intrinsic dynamics. Such interactions among embodied processes couple cognitive and motor constraints in the service of task performance. Thus it is no surprise that cognitive factors modulate the kinematics of motor coordination in laboratory performances (Abrams & Balota, 1991; Balota & Abrams, 1995; Gentilucci, Benuzzi, Bertolani, Daprati, & Gangitano, 2000; Zelinsky & Murphy, 2000).

*Self-organization* refers here to patterns of variability that appear in word pronunciation times (and other performance measures). These patterns reflect a system's intrinsic dynamics; they do not originate in external sources (Nicolis, 1989). The capacity for self-organization is corroborated in characteristic patterns associated with states of *self-organized criticality*. At or near a critical point, interactions between nearest neighbor processes are, effectively, extended across the entire system. "The system becomes critical in the sense that all members of the system influence each other" (Jensen, 1998, p. 3). *Criticality*, in this context, is indicated by scaling relations that imply coordination at all scales, a global dependence in the observed system.

### Pink Noise

Word pronunciations are complicated events. Articulation involves coordinated contractions of flexor and extensor muscle groups, nested within the molar coordination that we call the pronunciation. Similarly muscle contractions nest, and are nested within, body events having to do with neuromotor and vascular processes (Schmidt, Beek, Treffner, & Turvey, 1991). Such processes become coupled or entrained in the motor activities in which a person engages (Amazeen, Amazeen, & Beek, 2001; Amazeen, Amazeen, & Turvey, 1998).

Word pronunciations also intertwine processes on long time-scales, longer than the trial pace of a word naming experiment. For instance, conventional intuitions allow long-range fluctuations in motivation, vigilance, attention, and so on. But conventional intuitions don't take us far enough. Vertical coupling blurs structural and causal distinctions. It compounds processes as a complex irregular wave that fluctuates across the trials of a naming experiment. Waning fluxes contribute to slower naming times; waxing fluxes contribute to faster naming times. The empirical signature is *pink noise* that is observed in spectral analyses.



**Fig. 1.** *Panel A* portrays the average power spectrum for pronunciation times from twenty participants, for trial-series of 1100 individually presented monosyllabic English words (from Holden, Van Orden, & Turvey, 2001). Pronunciation time is the interval of time, in msec, between when a word appears and when a pronunciation triggers a voice key. Pronunciation times were kept in the strict trial-series order for spectral analyses, conducted in several ways with nearly identical results (cf. Chen et al., 1997; Gildea et al., 1995). Participants' slopes ranged from  $-0.11$  to  $-0.50$ , and the slope of the regression line portrayed in *Panel A* is reliably different from surrogate data,  $t(19) = 12.14$ ,  $M = -.30$ ,  $SD = .11$ . (Ideal pink noise has a slope of negative one and ideal white noise has zero slope, representing equal power at all frequencies.) *Panel B* portrays the average power spectrum for simple reaction times from ten (additional) participants, who each completed 1100 reaction time trials. Each trial began with a signal (#####) after which a participant quickly said /ta/, which triggered a voice key. Spectral analyses were conducted as for the previous trial-series. The slope of the regression line portrayed in *panel B* is reliably different from surrogate data,  $t(9) = 10.73$ ,  $M = -.68$ ,  $SD = .20$ . (Participants slopes ranged from  $-0.32$  to  $-0.99$ .) Likewise, the slopes for naming and simple reaction time are reliably different from each other,  $t(28) = 6.73$ . Pink noise is more prominent in tasks like simple reaction time that repeat identical trials (Gilden, 2001). It is less prominent in word naming because unsystematic fluctuations in trial-by-trial word properties decorrelate the pink noise signal.

If we graph each pronunciation time, in the trial order of the experiment, the data points fluctuate between fast and slow times. Connected data-points become a complex waveform that is approximated as a composite of waves spanning a range of frequencies. Pink noise is an inverse relation between the frequency of the composite waves and their amplitude (power) on log scales. Figure 1, *panel A*, illustrates this relation as it appears in trial series of pronunciation times. The term *pink noise* comes from a weak analogy to *pink light* that concentrates power at longer wavelengths. The analogy is weak because it fails to capture the scaling relation between power and frequency that implies coordination among scales. The relation between scales is “causally and interpretively bidirectional” (Lumsden, 1997, p. 35). “There is no characteristic time or frequency—whatever happens in one time

or frequency range happens on all time or frequency scales” (Schroeder, 1991, p. 112).

Scaling relations are observed in spectral analyses of *motor* performances like swinging pendula (Schmidt et al., 1991), tapping (Chen, Ding, & Kelso, 1997, 2001), and simple reaction time (Fig. 1, *panel B*). Pink noise is also found in *controlled-processing* cognitive tasks like mental rotation, lexical decision, visual search, repeated production of a spatial interval, repeated judgments of an elapsed time (Gilden, 1997; Gilden, Thornton, & Mallon, 1995), and simple classifications (Clayton & Frey, 1997; Kelly, Heathcote, Heath, & Longstaff, 2001). Here we illustrate the pink noise pattern in word naming, an *automatic* cognitive performance based on learned associations. The inclusive variety of these paradigms implicates vertical coupling generally in laboratory performances.

### Word Properties as Embodied Constraints

Distributions of pronunciation times present a different picture of self-organization. Self-organization is implicated by response time distributions whose slow tails fall off as inverse power laws—another scaling relation. We illustrate an inverse power law in a single participant’s distribution of word naming times, after we describe word properties as embodied cognitive constraints for word naming. We chose word naming as our illustration because neural network simulations of word naming implement simple control hierarchies (cf., Farrar & Van Orden, 2001; Kawamoto & Zemblidge, 1992; Masson, 1995).

Word properties are dynamic properties. For instance, the *frequency* of a particular word, on a particular day, in a particular laboratory, for a particular individual, refers to an idiosyncratic rate of recurrence. Word frequencies are calculated from samples of text, snapshots of discourse. A very common English word, like the word *the*, recurs so often that it appears in almost every snapshot. Any moderately sized sample of English is almost sure to include many instances of the word *the*. Less common words come and go across samples of all sizes.

Uncommon words greatly outnumber common words. So, whether or how often most words recur depends on which texts are read, that depends, in turn, on historical circumstances like a person’s regional culture and idiosyncratic choices. But rates of recurrence also change throughout a person’s lifespan as the terms *corsage* and *cataract* illustrate. Rates of recurrence even change among the designs of laboratory reading tasks (e.g., *repetition effects*). “The process to be measured changes even as we attempt to measure it.” (West & Deering, 1995, p. 29).

### Subword Relations as Embodied Constraints

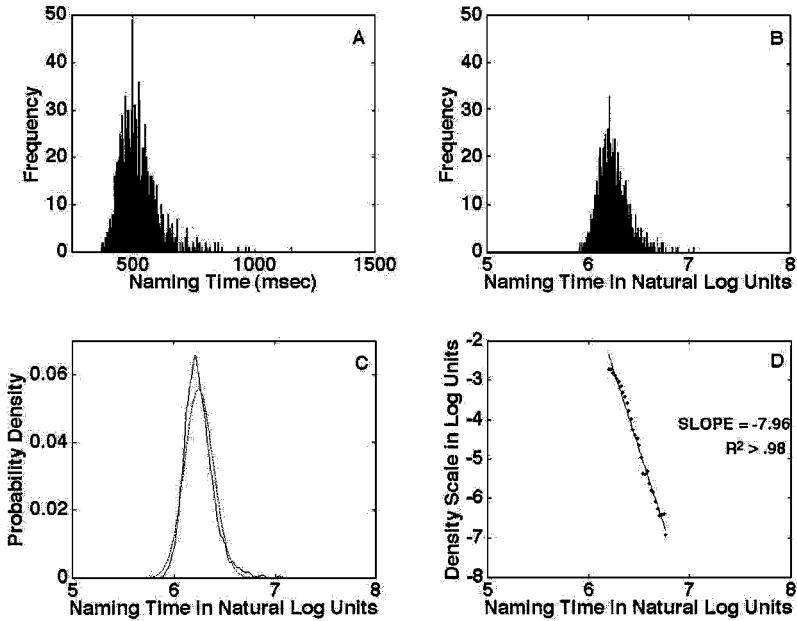
Subword relations add crucial detail to the pattern of recurrence. Subword relations piggyback on word recurrence but they, themselves, recur more often than the words they compose. Consequently, constraints that reflect subword relations are strengthened more often than whole-word relations (*mint*  $\Leftrightarrow$  *l<sub>mint</sub>*). Take the *body-rime* relation *\_int*  $\Leftrightarrow$  */\_intl*, in *mint*, for instance. This same body-rime appears in other words (e.g., *hint*, *lint*, *tint*); the body-rime *\_int*  $\Leftrightarrow$  */\_intl* would be found in all the snapshots of all the words it composes—more snapshots than any of the words taken individually. Constraints that attend on grapheme-phoneme relations are strengthened still more often (e.g., *i*  $\Leftrightarrow$  */i/*, *n*  $\Leftrightarrow$  */n/*, *t*  $\Leftrightarrow$  */t/*). They appear in many more snapshots than either body-rimes or words. Learning is distributed over many scales of information. Constraints live at every scale, which yields a hierarchy of constraints for word naming.

Control emerges on-line as the values of control parameters change from earlier to later dynamic regimes. Coherent body-rime and whole-word constraints grow out of competitive and cooperative dynamics at the scale of grapheme-phoneme constraints. On-line dynamics “grow” pronunciation constraints that attend on larger relations in interactions among smaller scale constraints. As larger scale constraints cohere, they also prune the active set of potential pronunciations at the smaller scale (cf. Shaw & Turvey, 1999).

Control emerges on-line, which extends the metaphysics of control hierarchy theory to embodied scales of information (Juarrero, 1999). But the constraints themselves derive from a vast hierarchy of statistical relations on different scales of culture and discourse. Thus, in effect, control of word naming extends outward into the structured environment of discourse and the idiosyncratic details of a participant’s history (Goldinger, 1996, 1998). This is the general point of our examples: “Stimulus” properties are constraints that interact as a control hierarchy (cf. Farmer, 1990).

### Response Time Distributions

Control parameters determine the stability of pronunciation options at the respective scales of learned information that are self-organized in the service of word naming. Stability determines the distribution of pronunciation times. In samples of words, embodied constraints, for a particular word on a particular trial for a particular person, are sampled unsystematically, as random variables (Van Orden, Holden, Podgornik, & Aitchison, 1999). Interactions combine constraints approximately as products. The product of



**Fig. 2.** *Panel A* presents a standard histogram of a single participant’s pronunciation times, from the experiment described in the previous figure caption. *Panel B*, presents a histogram constructed after a logarithmic transformation of the pronunciation times in *panel A*. The solid line in *panel C* represents the histogram in *panel B* as a probability density function (smoothed using a nonparametric Gaussian kernel density estimator, see Van Zandt, 2000). The dashed line in *panel C* is an ideal Gaussian curve, on the log scale, constructed using the empirical distributions’ mean and standard deviation. *Panel D* presents a scatter of points that run from the mode of the pronunciation time distribution down along its slow tail, and the power law regression line through the scatter of points (the scales of *panel D* are those of *panel C*, except *panel C*’s Y-axis has undergone a log transform).

two (or more) random variables is a lognormal distribution—a distribution that would appear *normal* on a logarithmic scale (Montroll & Shlesinger, 1982). Response time distributions from cognitive tasks resemble lognormal distributions (Luce, 1986; Ulrich & Miller, 1993), but they are not simply lognormal, as we explain.

Figure 2 presents a single participant’s distribution of pronunciation times from the word naming experiment. *Panel C* shows the smoothed probability density function after naming times undergo a logarithmic transformation, and the resemblance to a *normal distribution* (on log-linear scales). The dashed line in *panel C* represents an ideal *normal* curve constructed using the empirical distribution’s mean and standard deviation as parameters

(and normalized to occupy unit area within the interval). The previous linked assumptions explain why the distribution of pronunciation times resembles a lognormal distribution. However, despite the resemblance, the fit is rather poor, given that the parameters were estimated from over 1000 data points. The empirical distribution's slow tail broadens the ideal distribution, and introduces the discrepancy in the peaks of the two curves. Apparently, lognormal distributions do not fully accommodate the potential for nonlinear stretching of response time distributions.

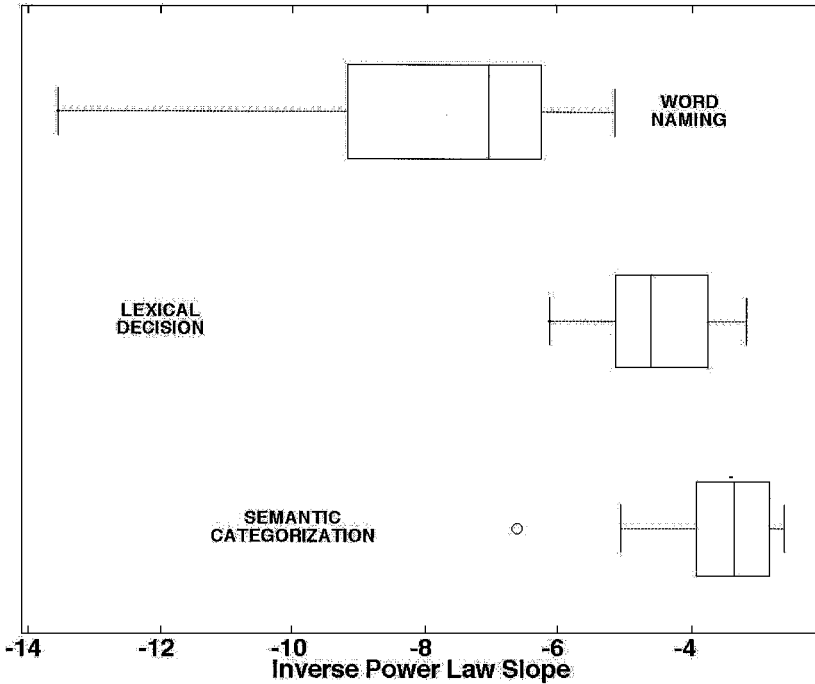
Natural processes that yield lognormal distributions tend toward inverse power laws as they become more complex. Nonlinear dynamics and positive feedback create the potential for iterative interactions that may *amplify* relaxation times for local instabilities, and *amplify the amplification*, and so on, which produces extreme slow response times. The implied continuum of distributions is defined by increasingly stretched, *amplified*, long tails. This pattern is corroborated if the long slow tail is well described by a power law (on log/log scales). Figure 2, *panel D*, presents a scatter of points taken along the slow tail of the pronunciation time distribution, and the power law regression line through the scatter of points—the scaling relation consistent with self-organization.

The participant whose pronunciation times appear in Fig. 2 produces a power law slope close to the median of the distribution of twenty participants' power law slopes (that ranged from  $-17.81$  to  $-5.85$ ). Steeper slopes come from distributions that are closely approximated by lognormal distributions, and shallower slopes come from distributions better approximated by inverse power laws along their long, stretched, slow tails. For example, a  $D$  statistic from a Kolmogorov-Smirnov test, that gauges the difference between the lognormal approximation and the empirical distribution, was positively correlated with the power law slope ( $r_s(18) = .70, p < .05$ ). This pattern held for parametric fits as well. We speculate that the narrower (more stable) distributions come from more skilled readers, because they can rely on well tuned internalized constraints.

### Intentionality

Different tasks entail different intentions to perform, and different intentions imply different hierarchies of constraints, within which performances self-organize (Van Orden & Holden, 2002). Control hierarchy theory accommodates intentions as extraordinary boundary conditions—constraints that change on longer times scales than laboratory performances (Kugler & Turvey, 1987). Participant intentions to perform as instructed grow out of embodied dynamics on time scales of social discourse and language





**Fig. 3.** Boxplots of power law slopes, computed as in *Fig. 2*, from individual participants' distributions of correct response times from word naming, positive "word" lexical decisions, and positive "exemplar" semantic categorizations. Fifteen different participants were assigned to each of the three tasks. Each task presented the same 168 target words (from typicality norms, Uyeda & Mandler, 1980). The center-line of each box plot corresponds to the *median* slope, the left and right sides correspond to the *first* and *third quartiles* of participants' slopes, and the dashed "whiskers" show the range of slopes with outliers plotted as circles. Precise slopes depend on parameters that are chosen in fitting the distributions. We treated all distributions identically and used nonparametric statistics to distinguish them. What is important is that slopes become shallower as a function of task. A nonparametric Mann-Whitney  $U$  test reliably distinguishes the distribution of slopes for word naming from the distribution of slopes for lexical decisions,  $Z_U = 4.42$ ,  $p < .05$ . Likewise, the distribution of slopes for lexical decisions is reliably different from the distribution of slopes in semantic categorization,  $Z_U = 2.47$ ,  $p < .05$ .

comprehension and limit behavioral options on the time scales of laboratory trials (Juarrero, 1999). As intentional constraints cohere, they also prune the set of behavioral options.

The box plots in *Fig. 3* illustrate distributions of power law slopes calculated for each participant to another set of target words that each appeared identically in three widely used laboratory reading tasks: *word naming*, *lexical decision* (respond "yes" if the target is an English word), and *semantic*

*categorization* (respond “yes” if the target is a category exemplar). Notably, the distributions of power laws that characterize the task performances change reliably across the three tasks—the range of participants’ power law slopes, within tasks, differs across tasks, which implies that the tasks themselves differ in complexity.

Different tasks emphasize different constraints, which explains why interactions among tasks and cognitive factors confounded additive factors logic. Word naming emphasizes “bottom up” relations between words’ spellings and their pronunciations. Constraints that attend on these relations function generally in reading, and their relative stability is the key to successful reading (Pennington, 1991). Participants’ capacities for word naming appear to range from skilled readers, who produce more constrained log-normal behavior, out to less skilled readers for whom word naming is a complex task (Holden, 2002). Lexical decisions emphasize “top down” relations between words’ pronunciations and their spellings (the inverse of word naming), less stable relations that pertain more to writing and spelling than to reading (see Bosman & Van Orden, 1997, for a review). Categorization emphasizes more or less familiar relations between semantic categories and word meanings (e.g., Larochelle, Richard, & Soulières, 2000). Participants produce more complex behavior—shallower inverse power laws—in the lexical decision and categorization tasks. Different tasks require different intentions to perform, and task specific intentions imply task specific control hierarchies.

### A PROPER METAPHYSICS

Core assumptions require empirical support, a basis in reality. Scaling relations motivate assumptions of control hierarchy theory, and scaling relations are generally observed in laboratory performances. Core assumptions that correctly characterize a system’s intrinsic dynamics tell us what kind of system we deal with. They define the kind of research program that may be appropriate for the system under study. For example, scaling relations encourage a programmatic focus on parameter dynamics—factors that determine the stability of behavioral options (Kelso, 1995).

Core assumptions must also embrace the salient aspects of a system. The more inclusive metaphysics of control hierarchy theory makes a place for intentionality. Outside the laboratory, attribution of intentions is the basis for meaningful interpretation of behavior (Gibbs, 1999; Juarrero, 1999; Searle, 1992). A proper metaphysics for cognitive performance must likewise accommodate the intentional basis of laboratory participation.

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