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Intentional Contents and Self-Control

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Conventional research programs adopt efficient cause as a metaphor for how mental events affect behavior. Such theory-constitutive metaphors usefully restrict the purview of research programs, to define the space of possibilities. However, conventional research programs have not yet offered a plausible account of how intentional contents control action, and such an account may be beyond the range of its theoretical possibilities. Circular causality supplies a more inclusive metaphor for how mental events might control behavior. Circular causality perpetuates dynamic structures in time. Mental contents are seen as emergent dynamic constraints perpetuated in time and vertically coupled across their multiple timescales. Intentional contents are accommodated as extraordinary boundary conditions (constraints) that evolve on timescales longer than those of motor coordination (Kugler & Turvey, 1987). Intentional contents, on their longer timescales, are thus available to control embodied processes on shorter timescales. One key assumption—that constraints are vertically coupled in time—is motivated empirically by correlated noise, long-range correlations in the background variability of measured laboratory performances.

"The classification of behavior in categories, the limits of which are rigidly fixed, together with the adoption of a specific terminology, frequently serves to check scientific advance. … The terms 'reflex,' 'involuntary,' 'voluntary' and 'automatic' are more than classificatory designations; they have come to carry a burden of implications, philosophical, physiological and psychological. … *It is essential that they be used with caution, and that the hypothetical implications which they have acquired during the 17th and 18th centuries be regarded as provisional only*" (Fearing, 1930/1970, p. 253).

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Several years ago, the cover of the *American Psychologist* announced: "Behavior—It's Involuntary." The banner heading referred to articles in the "Science Watch" section. The articles summed up studies reporting that mostly involuntary, automatic processes underlie human behavior ("Science Watch," 1999). The conventional distinction between automatic versus intentional, controlled, voluntary, willed, or strategic behaviors stems from Descartes' famous analogy to water-driven motions of garden statues. Descartes proposed that some actions of living beings might originate in clocklike automata. Contemporary thinkers amend his proposal and claim that most human behavior is automatic.

A nagging concern, however, is the perpetual absence of reliable criteria by which to distinguish automatic behavior. For example, Fearing's (1930/1970) historical review notes that even a knee-jerk reflex, a classic automatic behavior, is difficult or impossible to distinguish from voluntary behavior. He concluded, at the time of his review, that no reliable criteria exist by which to distinguish automatic behavior. Fearing's conclusion applies to current studies as well. They remain stuck on the same issue. It is still the case that no generally accepted definition exists that can distinguish automatic laboratory performances from intentional performances. Now, as in the past, definitions of the term *automatic behavior* lean precariously and exclusively on intuition and a few illustrative laboratory performances (Vollmer, 2001).

The Stroop effect is an example of autonomous automatic processing. The term *autonomous* means that the Stroop effect has its basis in an involuntary process that operates outside of, and possibly in opposition to, a laboratory participant's goals or intentions. A Stroop experiment presents a color word such as *red* or *blue* printed in red ink (for instance), and the participant names the color of the ink. The Stroop effect refers to faster color naming times in the congruent "red on red" condition than in the incongruent "red on blue" condition (Stroop, 1935). Presumably, the color words' "names" are automatically generated and reinforce (or interfere with) color naming, irrespective of participants' intentions. The Stroop effect is the most widely cited example of automaticity (MacLeod, 1992).

Several definitions have been proposed to capture the essential character of examples such as the Stroop effect. Criteria for automaticity have included (a) absence of voluntary control (as noted previously); (b) absence of resource limitations, which means that resource-limited processes such as attention cannot be the essential basis of automaticity; and (c) ballistic, whereby effects proceed automatically and inevitably from their causes, their stimulus triggers—like a bullet fired from a gun. All these criteria are challenged by results from careful empirical studies. For instance:

> Contrary to what has been frequently assumed … automatic processing is sensitive to resource limitations [and] can be controlled, at least to some extent … which in turn challenges the criterion of (the absence) of volition. This has led some to question the usefulness of the very concept of automaticity. (Tzelgov, 1997, p. 442)

Presently, the term *ballistic* remains in play, but even the Stroop effect is demonstrably not ballistic. A ballistic process should not be affected by factors extraneous to the trigger events. Nevertheless, Besner and his colleagues demonstrate reduced or absent Stroop effects after small extraneous changes, such as restricting the colored ink to only one of *blue's* letters (Besner & Stolz, 1999b; see also Bauer & Besner, 1997; Besner & Stolz, 1999a; Besner, Stolz, & Boutilier, 1997).

So what do we talk about when we talk about automaticity? Apparently, no one knows for sure. Juarrero (1999) described a similar failure by philosophers of action to adequately distinguish automatic acts. She attributed this failure to "a flawed understanding of … cause and explanation" in intentional behavior. Juarrero proposed a philosophical view of intentionality in which the meaningful content of "intentions *flow* into behavior" and "unequivocally inform[s] and constrain[s] behavior" (p. 103). Like Juarrero, we give priority to intentionality and take seriously the protracted failure to adequately define automatic behavior. In other words, we take issue here with the conclusion so confidently displayed on the cover of *American Psychologist* ("Science Watch," 1999).

Laboratory performances are never involuntary, in the conventional sense, but are by their very nature intentional (Gibbs & Van Orden, 2001). We consider next why laboratory performances are always intentional, and then explain why conventional research programs are biased nevertheless to discover automatic behavior. After that we describe more inclusive metaphysical assumptions that may accommodate intentional control.

INTUITIVE INTENTIONALITY

The view of behavior as mostly involuntary is a bit strange. It suggests a robot world in which mindless individuals stagger along trajectories that change in billiard-ball-type "collisions." In the robot world, a scientist's clever external stimulation of the robot would be perpetuated through connected modules in the robot brain and output as behavior. Change always refers eventually and exclusively to external sources; "mental processes … are put into motion by features of the environment and … operate outside of conscious awareness and guidance" (Bargh & Chartrand, 1999, p. 462). That is what it means for behavior to be automatic, in the conventional metaphor.

Lacking intentionality, the robot world appears incomplete compared to the meaningfully animated and purpose-filled world in which we actually live (Searle, 1992; Velmans, 2000). In the world we occupy, people generally interpret the behavior of others as intentional, to make sense of their behavior. We evaluate intentions in all domains of discourse (Gibbs, 1999). Laboratory performances are themselves intuitively intentional, and scientists show the same disposition as anyone else to see them that way.

Take the typical scenario of a psychology experiment, for instance, which may discover automatic behavior. A participant is told the response options and instructed to respond quickly and accurately. But not every person actually behaves as instructed. A rare uncooperative person may produce the same response on every trial. Someone else, equally disagreeable, may produce a nonsensical pattern of responses, ignoring the instruction to respond accurately, or they may dawdle in the task, responding too slowly to produce usable response-time data. Investigators actually eliminate data from analyses on the basis of such idiosyncrasies, an implicit evaluation of the participant's disagreeable intentions. The point of this example, however, does not concern uncooperative performances per se, but their opposite. The simple fact that scientists are disposed to evaluate participants' intentions contradicts (or at least qualifies) any claim that performances are automatic. The contrast with uncooperative performances makes more salient the spheres of intentionality that surround every cooperative performance (Vollmer, 2001). Otherwise, the attribution of uncooperative performance is paradoxical.

To be fair, the conventional term *intentional automatic processing* seems to circumvent the paradox. Speeded word naming is an example of intentional automatic processing. In a speeded naming experiment, a participant is presented with a printed word and the instructions to read it aloud quickly and accurately. Similar to the Stroop effect, speeded word naming is based on automatic retrieval of words' names. Thus the automatic performance is directly aligned with the task instructions, the source of directed intentions to perform speeded word naming.

The conventional view of speeded word naming seems to make room for both intentions, which initiate behavior, and automatic processes, which follow from those intentions (Jacoby, Levy, & Steibach, 1992). Intentional contents are equated with representations, causal states along the same lines as the representations in automatic processes. To make scientific sense, however, this use of the term *intention* must entail empirical methods that can dissociate intentions from other representations. Otherwise, its use merely pretends to address intentionality, and ducks the issue altogether. (We discuss empirical methods in the next section.)

But if it is so intuitive that laboratory performances are intentional, then why do laboratory studies discover that behavior is mostly automatic? Conventional research methods presume the limited view of cause and effect in which representations cause behavioral effects. Consequently, when they address intentionality, they must misread intentions as mediating, causal states of mind—states of mind with causal powers no greater than colliding billiard balls or chains of falling dominoes (Gibbs & Van Orden, 2001). Conventional methods are blind to other possibilities. We claim that this limited view of cause and effect leads inevitably to the conventional emphasis on automatic processes (cf. Wegner & Wheatley, 1999). The next section spells out the basis of our claim in conventional metaphysics.

CONVENTIONAL METAPHYSICS

Most research efforts in cognitive psychology concern the series of mental representations that result in behavior. Structural hierarchy theory distinguishes such 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. A necessary assumption is that the Chinese boxes are vertically separated in time. *Vertical separation* means simply that *larger* boxes change states on *longer* timescales. The crucial point of vertical separation is that changes on different timescales may be separated in terms of their causal implications—we may isolate causal properties on different timescales.

For instance, some scientists believe that linguistic competence changes on the *very long* timescale of evolution, whereas the advent of literacy refers to a separate *long* timescale of cultural change. Linguistic competence changes on a longer timescale than culture, and both change on longer timescales than mental events. If so, then they present a static background for states of mind in an automatic action such as speeded word naming in a word naming experiment. In turn, mental states provide a static background for neural events, interactions that occur on the still-shorter timescales of the nervous system. The timescales are sufficiently separate that changes on long timescales appear frozen in time when seen from the perspective of shorter timescales.

Neural interactions themselves contribute unsystematic variability to measurements of mental events on longer timescales. Interactions on the very short timescale of the nervous system contribute random variability around the average pronunciation time to a printed word, for example, as measured in a word naming experiment. Methods for measurement of mental effects, on their characteristic timescale, are simply too coarse-grained to pick up systematic variability on the much shorter timescales of neural processes (and other bodily processes on very short timescales). Thus neural events show themselves as a background of unsystematic variability—*uncorrelated noise* (which becomes important in a later section).

The basic premise of structural hierarchy theory is that discernible mediating causal states, or *representations,* exist and may be described (see also Markman & Dietrich, 2000). Take speeded word naming, for instance. A component process of sensation may represent optical features of a stimulus word, which perception takes as input to supply representations of the word's letters. Letter representations, in turn, serve as input to a component process of word recognition that may represent the pronunciation of the particular word. The representation of a word's pronunciation, in its own turn, triggers elements of articulation, which we observe as the pronunciation response.

Vertical separation is one of several assumptions that are crucial for an analysis of mental states as mediating causes. If mental events unfold on their own, separate, characteristic, timescale, then total elapsed response time can be parsed into the time course of component events that preceded a response. A separate characteristic timescale allows a sequence of mental effects to be treated as a causal chain distinct from effects on longer and shorter timescales (A. Newell, 1990). Thus, vertical separation must be true a priori if we are to dissociate mental events from other phenomena of nature.

Another assumption must be true so that we may dissociate mediating representations in measured behavior. Component processes must interact approximately linearly; an assumption Simon (1973) dubbed *loose horizontal coupling.* For example, additive factors method can be viewed as a test for loose horizontal coupling. Experiments with several experimental manipulations in factorial designs provide the opportunity for interaction. If the effects of two or more factors are strictly additive, then the manipulations satisfy the superposition principle. They selectively influence distinct components (Sternberg, 1969).

Loose horizontal coupling respects a very old intuition about human behavior—that it originates in *component-dominant dynamics* among specialized component devices of mind: sensation, perception, memory, language, and so on. As the term *component-dominant* suggests, the intrinsic dynamics of the components—dynamics inside the components—dominate interactions among components. This may ensure the integrity of component effects. It encapsulates component effects such that they can be recovered in the measured behavior of the whole. Thus, component effects may be individuated in measurements of a system's behavior. Component effects that are reliably individuated in measurements of a person's behavior—as with additive factors method—reduce to the causal properties of the components themselves.

Notably, additive factors method tests the "adequacy of the assumptions that underlie its use," whether response time actually entails loosely coupled components (Pachella, 1974, p. 50). This sets additive factors method apart. Other methods that would reduce behavior to mediating states include no test of their assumptions. Other reductive methods rely on a priori knowledge of the components that they seek to justify the search. Examples include subtractive methods and dissociation analyses popular in cognitive neuroscience (for a critique, see Uttal, 2001). But how does one know a priori whether laboratory tasks differ simply by distinct mental components, or which components a task would entail, or whether manipulations refer to distinct components? Additive factors method does not require a priori knowledge of mental states; it requires only the assumption that components are loosely coupled, and it tests this assumption each time it asks whether component effects are additive. Thus, additive factors method illustrates a scientifically conservative test of whether laboratory performances implicate a nearly decomposable system.

But what about intentionality? Simon (1973) did not discuss intentionality, but the assumptions of vertical separation and loose horizontal coupling allow only two choices for intentionality: Either intentions fit as a link in a causal chain of mental representations, or intentionality is not a proper subject for scientific discourse. No other choices exist within this framework. It is in this sense that efficient cause serves as the theory-constitutive metaphor for how we think about cause and behavior. Vertical separation and loose horizontal coupling extend the metaphysics of billiard-ball causality (efficient cause) to mental events. Actions are viewed as end states that follow from chains of mediating representations. If so, then intentions must be representations. Otherwise there is no entry point for intentions in the analysis.

We mentioned Juarrero's (1999) philosophical argument that intentions, as a basis of ongoing control, cannot possibly reduce to mediating causal states (see also Greve, 2001). If she were correct, then we would expect that empirical studies must fail to justify mediating causes in human performance. As a matter of fact, nonadditive effects are the rule in cognitive experiments, not the additive effects that would corroborate loose horizontal coupling. A vast nexus of nonadditive interactions, across published experiments, precludes assigning any factors to distinct components.

This is true in particular for the vast literature that has grown out of laboratory reading experiments (Van Orden, Pennington, & Stone, 2001). Performances attendant on reading are conditioned by task demands, culture, and language, whether they come from tasks that require controlled processing or from automatic performances such as speeded word naming. Consider the implications within the guidelines of additive factors logic. Cognitive factors in reading are neither individuated as causes, nor causally segregated from the context of their manipulation—task, culture, or language. No reliable evidence exists that may individuate any mediating representations in human performance; no evidence exists that would motivate the core assumptions of structural hierarchy theory.

LIVING SYSTEMS

Conventional research programs have failed, so far, to produce empirical corroboration for the assumptions of structural hierarchy theory. However, do not confuse these failures with naive falsification of vertical separation and loose horizontal coupling. The failures up until the present moment could mean that we have not yet correctly described the set of factors that do combine linearly in performance. A correct parsing of performance using correctly manipulated factors could yet discover elementary additive interactions. Likewise, do not take the outcome, so far, as falsification of representation. The question is not whether there are mediating states, but whether a research program is feasible that must equate mediating representations with units of cognitive performance. Said slightly differently, we ask whether a research program is feasible that must recover component effects in measurements of behavior for a reduction to component causes.

We expect that the conventional research program will continue its failure to corroborate core assumptions, because it cannot accommodate the complex autonomous behavior of living beings. In contrast, a more contemporary and inclusive view of causality recognizes a basis for self-control in complexity theory and self-organization (Juarrero, 1999). From this perspective, intentional acts are observed every time a person performs a laboratory task (Kugler & Turvey, 1987). This and the sections that follow introduce a more contemporary metaphysics that finds a place for living systems.

Living systems are complex systems; increasingly complex dynamic structure makes possible increasingly autonomous behavior. Autonomous behavior originates in positive feedback processes. Positive feedback processes include billiard-ball causality, but they do not reduce to billiard-ball causality. Life itself originates in the circular, positive feedback process of chemical autocatalysis. In autocatalysis, the output of a chemical reaction becomes, in turn, its input and catalyzes the same reaction. Autocatalysis thus perpetuates the reaction in cycles of chemical reproduction. The chemical reaction, itself, appears as a coherent, self-organized, iterative structure—a cycle perpetuated through time.

Contemporary evolutionary theory treats chemical autocatalysis as an archetype. The units of selection in natural selection, for instance, are positive feedback processes of metabolism, development, and behavior. Such units are metaphorical extensions of autocatalysis, with cycles that recur on longer timescales (Depew & Weber, 1997). Circular causality—illustrated by archetypal chemical autocatalysis—presents us with an alternative theory-constitutive metaphor. Positive feedback perpetuates dynamic structures in time, on their own timescale. The timescale of a simple dynamic structure corresponds to the time course of its cycles. Different dynamic structures may live on widely divergent timescales.

Positive feedback among structures on different timescales adds another dimension to this metaphor. For example, a single complex system may evolve simultaneously on many timescales. The additional dimension may be directly contrasted with Simon's (1973) metaphysics. In Simon's metaphysics, vertical separation partitioned nature among segregated, characteristic timescales. Vertical separation implied that mental events would appear as random fluctuations, in measurements of events on an evolutionary timescale, for example. But feedback processes in complex living systems are vertically coupled on different timescales. As a consequence, fractal patterns of long-range correlation may emerge, which can be discovered in a system's behavior (i.e., *correlated noise,* or *fractal time,* which we describe shortly).

Perhaps a made-up concrete example of vertical coupling can give a better feel for the contrast with vertical separation. Suppose that human performances (e.g., invention, consumption) attendant on mental events may reverberate through cultures (e.g., industrialization, consumerism) and environments (e.g., pollution, deforestation, global warming). Such reverberations could alter the niches that the environment affords for us, and for the species with which we coevolved, and alter the relations among species. A *fitness landscape* summarizes the complex web of these relations; more stable relations are represented as occupying higher, fitter peaks (Bak, 1996; Goodwin, 1994; Kauffman, 1995). Sufficient change will elicit new relations (e.g., new species), changes in existing relations (e.g., altered phenotypes, invasion of one species' niche by another species), or eliminate the potential for previously viable relations (e.g., precipitate small or large cascades of extinction). This evolutionary process yields an ever-changing fluid topology of fitness.

Vertical coupling among events on multiple timescales allows the previous linked changes to occur. Sufficient change in bottom-up "microlevel" interactions among individuals may alter the possibilities for top-down "macrolevel" control of these interactions. Thus, changes in the relations among species on their long timescales are inherently coupled to changes in the relations among individuals acting on shorter timescales. Vertical coupling takes into account that relations among species are emergent products of interactions among individuals (and environments). *Control parameters* index emergent, self-perpetuating, abstract relations among individuals and groups of individuals. Abstract relations come into or out of existence if the balance among constraints changes sufficiently.

Control hierarchy theory summarizes the network of complex relations in an abstract hierarchy of control parameters. Juarrero (1999) proposed that intentional contents are part of this endlessly evolving hierarchy of control parameters. Intentional contents emerge and are perpetuated in time via circular causality. Because they are perpetuated in time, they are available to constrain control processes on shorter timescales. Thus, intentional actions self-organize in embodied, vertically coupled, control processes.

CONTROL HIERARCHY THEORY

Structural hierarchy theory was concerned with the causal status of mental structures. To map out the functional organization of a cognitive system would be to map out the causal interactions among the components of the system—the system's flowchart. To do so would require knowing the states (representations) associated with each component and how representations are causally dependent on each other. As such, structural hierarchy theory was concerned exclusively with causal relations in the form of efficient causes. Again, efficient cause served as its theory-constitutive metaphor for how to think about cause and behavior.

In the more contemporary picture, we substitute vertically coupled feedback processes, summarized in a hierarchy of control parameters, for Simon's (1973) vertically separated Chinese boxes. Control hierarchy theory draws on the theory-constitutive metaphor of *circular causality* in the form of positive feedback, a form of *self-cause* (Pattee, 1973). This metaphor may be extended to laboratory performances that are also embedded in the complex ecology of living systems. Feedback across timescales reaches all the way out, into the long timescales of culture (e.g., social constraints that emerge as laboratory etiquette) and evolution (e.g., capacities for categories of action such as articulation), and all the way in, to the very short timescales of the nervous system (and so on). Relations among levels in the hierarchy are "causally and interpretively bidirectional" (Lumsden, 1997, p.

35). Laboratory performances emerge from this endlessly evolving hierarchy of vertically coupled processes.

Most important, for our present argument, control hierarchy theory makes a place for participant's intentional contents in explanations of cooperative and uncooperative behavior. Intentional contents supply *exceptional boundary conditions* for behavior (Kugler & Turvey, 1987). For example, it is intuitive that instructions and other aspects of laboratory control define "boundaries" that limit the behavioral options of participants. That is why we so carefully prepare detailed laboratory scripts to guarantee that participants perform as planned. Self-organizing systems may perpetuate their dynamic structure in time (on multiple timescales), which invokes again the analogy with autocatalytic processes and the theory-constitutive metaphor of circular causality. Likewise, intentional contents that evolve (self-organize) on longer timescales are perpetuated in time relative to control processes on shorter timescales, which makes them available to limit the degrees of freedom for interactions among processes on shorter timescales.

Intentional contents emerge out of, and control, cognitive performances. Juarrero (1999) describes at length how intentional contents reduce degrees of freedom in a human capacity for self-organization. Intentions modify a system's phase space and restrict the potential set of trajectories through that space. In this way, intentional contents reduce the degrees of freedom for behavior and thereby construct specialized devices—as laboratory participants may make of themselves specialized laboratory devices: simple reaction time devices, word naming devices, or whatever, as required by task instructions (Kugler & Turvey, 1987).

> According to nonlinear, far-from-equilibrium science … systems are created from interacting components, which they then, in turn, control. As a result of this strange loop relation between parts and wholes, these dynamical systems are not mere epiphenomena; they actively exercise causal power over their components. (Juarrero, 1999, p. 131)

Instructions, as directed participant intentions, set boundaries and limit the options for laboratory performance. Agreeable intentional performances self-organize within the understood boundaries. This capacity to sustain directed intentions for laboratory performance emerges within a control hierarchy of vertically coupled constraints. Unlike Simon's (1973) Chinese boxes, however, vertically coupled constraints fluctuate and interact across many timescales, including timescales within the time course of an experiment. This core assumption can be tested. It sets us up to expect correlated noise in measurements of human performance.

CORRELATED VERSUS UNCORRELATED NOISE

Self-organization concerns the integrity of a whole that may become a specialized device, as circumstances require. In a self-organizing system, interactions among component processes may dominate the intrinsic dynamics of the components themselves—call this *interaction-dominant dynamics.* When interactions among component processes dominate their intrinsic dynamics, then the behavior of the whole is different from the sum of its parts. Self-organization requires these more flexibly coupled dynamics (Jensen, 1998).

Intentional contents fluctuate on timescales longer than the trial-by-trial pace of a laboratory experiment—longer than the trial pace at which response times are taken, for example. These and other fluctuations on longer timescales are the source of long-range correlations in the background variability of performance measures—*correlated noise* (Van Orden, Holden, & Turvey, 2002). We are particularly interested in *pink noise,* a statistically self-similar (fractal) pattern of long-range correlations in trial-to-trial variability. Pink noise has been observed previously in response-time studies. Figure 1a illustrates pink noise as it may appear in a participant's trial series of simple reaction times (prepared for spectral analysis—see figure caption).

Pink noise is also called *fractal time.* Fractal objects such as pink noise occupy fractal dimensions that lie "in-between" the dimensions of more familiar, ideal, geometric objects such as lines and planes. Variability in response time can be conceptualized to partly occupy, or leak into a next higher Euclidean dimension. Figure 1's series of reaction times, graphed in the ordered series in which they were collected, appear as points connected by a line—a *trial series.* Clearly, if we could "pull" this line taut, and make it straight, then it would have a Euclidean dimension of 1. But any departure from the ideal form of a line begins to occupy or leak into the next higher, second, Euclidean dimension (likewise, departures from an ideal plane leak into the third dimension, and so on). In this sense, variability in response time may occupy area and will have a dimension between an ideal one-dimensional line and an ideal two-dimensional plane. The more jagged and irregular the graph of response times, the more area it occupies.

Conventional analyses require that background variability is exclusively uncorrelated noise, uniformly distributed Gaussian noise—*white noise*—as prescribed by structural hierarchy theory. Otherwise measurements must be "corrected" to create statistical independence between successive trials (West & Hepworth, 1991). White noise yields a jagged and irregular line with a fractal dimension of 1.5 that gauges the extent to which it occupies two-dimensional space. The fractal dimension of white noise derives from a familiar scaling relation, which may serve to introduce less widely appreciated possibilities. The scaling relation is familiar from the equation for the standard error of the mean (*SE*)—the standard deviation of a sampling distribution of means, where each sample mean characterizes a distribution drawn from a standardized, homogeneous, Gaussian, independent, random variable.

$$SD_{\mathrm{Pop}}/\sqrt{N} = SE \tag{1}$$

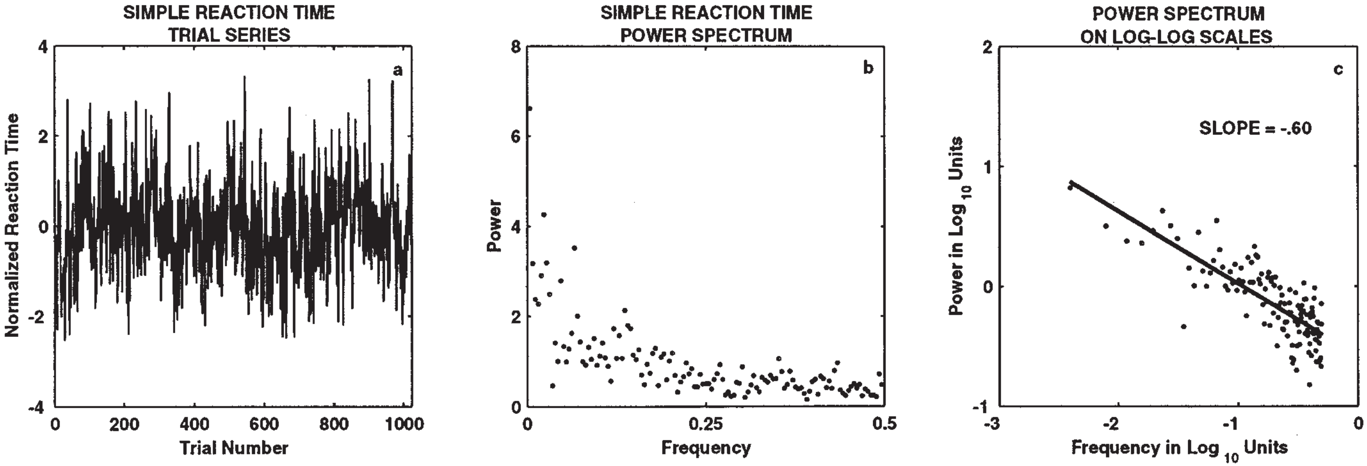

FIGURE 1 Panel A displays the pattern of pink noise in a trial series of simple reaction times. The *x* axis is the trial number, in the order of the experiment, and the *y* axis is reaction time. To prepare the series for spectral analysis, reaction times were normalized to have a mean of zero and unit standard deviation (after linear and quadratic trends were removed). Panel B depicts the spectral analysis of the same trial series. Like Fourier analysis, a spectral analysis fits a large set of sine (and cosine) waves to approximate a complex waveform. The *x* axis of Panel B indexes the period of oscillation (frequency), and the *y* axis indexes amplitude (relative height) of each component wave. Panel C represents the results of Panel B's spectral analysis after a transformation to a double logarithmic scale. The slope of the line (–.60) in Panel C estimates an inverse power law that describes the relation between frequency and power (amplitude squared) of the component oscillations. Slopes near –1 suggest relatively strong positive correlations across a wide range of frequencies. The observed slope is consistent with the hypothesis that fluctuations in reaction time comprise a nested, statistically self-similar pattern—pink noise, fractal time. (These data from one participant come from a study that contrasted several participants' data with yoked surrogate data in analyses that concluded in favor of pink noise; Van Orden et al., 2002.)

SD_{Pop}, in equation (1) is the population standard deviation for the sample size N. Standardized SD_{Pop} equals one, which allows Equation (1) to be rewritten as:

$$1/\sqrt{N} = SE \tag{2}$$

Equation (2) is a scaling relation between the index of variability SE and sample size N. Taking the logarithm of both sides of equation (2) yields:

$$-0.5 \times \log(N) = \log(SE) \tag{3}$$

Equation (3) describes how error in the estimation of the mean of a Gaussian variable is reduced as sample size increases. A plot of this scaling relation, on log-log scales, is a straight line with slope –0.5 (the dashed line in Figure 2). The

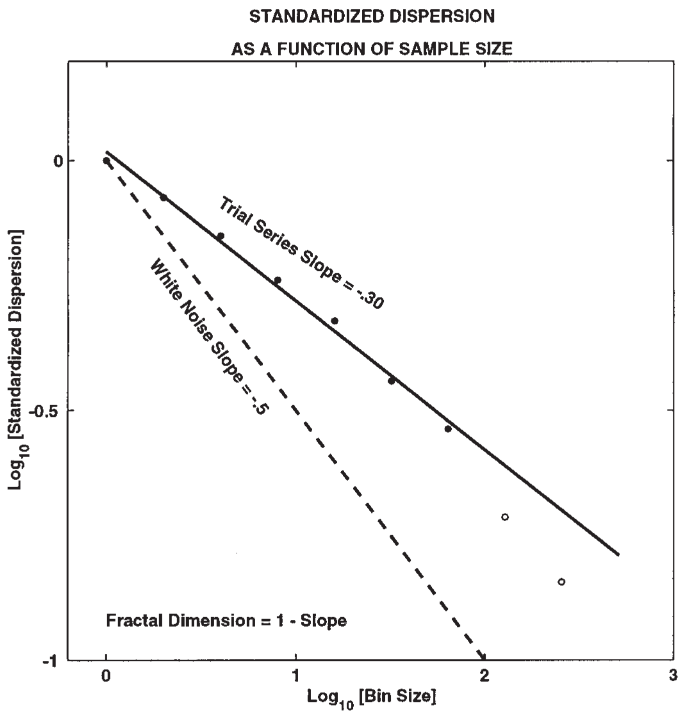

FIGURE 2 Dots represent paired values of log[bin size] and log[Standardized Dispersion] from the two rightmost columns of Table A1. The x axis indexes the logarithm of bin size (sample size; see Appendix), and the y axis indexes the logarithm of corresponding values of standardized dispersion. The dashed line has a slope of –.5, which would be expected if reaction times were statistically independent from trial to trial. The filled circles are the basis of the linear least squares fit regression line (on the log scales). The filled circles correspond to the values in Table A1 that are underlined. The open circles represent values that were excluded from the regression. The solid regression line has a slope of –.30. The fractal dimension of the trial series is 1.30, consistent with pink noise.

fractal dimension of white noise is calculated by subtracting this slope from 1, its Euclidean dimension (Bassingthwaighte, Liebovitch, & West, 1994). The standard error of the mean thus illustrates how uncertainty in an estimated sample population parameter scales as a function of sample size. Measured variability of a *homogeneous* uncorrelated signal, such as white noise, stabilizes relatively quickly, as sample size is increased.

In contrast to white noise, we may find nested, correlated, statistically self-similar fluctuations—pink noise. Nested long-range correlations yield a graphical picture of response times that is less jagged than white noise, leaks less into the second Euclidean dimension, and yields a fractal dimension closer to 1. Correlated noise implies that samples of all sizes tend to "hang together," which leads to counterintuitive statistical properties. As larger samples are considered, variability tends to increase rather than stabilize and may lead to a notable limiting case in which the variance is undefined (Bassingthwaighte et al., 1994). *Heterogeneity* in variability measured at different scales destabilizes parametric measurements and creates a challenge for conventional statistical methods that must assume stable parameters.

Relative dispersion analysis is a robust method to estimate fractal dimension (Eke et al., 2000). Dispersion analysis is related to the renormalization group procedures used by physicists to study critical point behavior (e.g., see Bruce & Wallace, 1989). Van Orden et al. (2002) used dispersion analysis to gauge how variability scales with the size of adjacent samples in trial series of simple reaction times and speeded word naming times. This fractal method repeatedly resamples the trial series using sampling units of different sizes to estimate the fractal dimension of a trial series. The fractal dimension of variability in the trial series gauges the scaling relation between variability and sample size, whether variability converges fast enough, as sample size increases, to yield stable population parameters.

The results of a dispersion analysis on the data from Figure 1 are plotted in Figure 2, as described in the Appendix. The solid line represents the least squares regression line for the relation between the relative dispersion (*y* axis) and sample size (*x* axis, i.e., *bin size;* see Appendix). The dashed line in the figure has a slope of –.5, and represents the ideal slope of white noise—compare to the previous Equation (3). The slope of the solid line is –.30, which implies a fractal dimension of 1.30. Empirical fractal dimensions of pink noise may range between 1.5 (white noise) and 1.2 (ideal pink noise). Van Orden et al. (2002) found fractal dimensions consistent with pink noise in almost every participant's trial series of simple reaction times and speeded word naming times. (One participant's simple reaction time trial series yielded a fractal dimension that fell on the boundary that distinguishes pink noise from brown noise.)

Correlated noise has been observed widely in spectral analyses of motor performances, such as swinging pendula, tapping, and human gait (Chen, Ding, & Kelso, 1997, 2001; Hausdorff et al., 1996; Schmidt, Beek, Treffner, & Turvey, 1991). It is found in controlled processing tasks, such as mental rotation, lexical decision, visual search, repeated production of a spatial interval, repeated judgments of an elapsed time, and simple classifications (Aks, Zelinsky, & Sprott, 2002; Clayton & Frey, 1997; Gilden, 1997; Gilden, Thornton, & Mallon, 1995; Kelly, Heathcote, Heath, & Longstaff, 2001). And the word naming experiment of Van Orden et al. (2002) demonstrates correlated noise in an automatic cognitive performance based on learned associations. Correlated noise is most pronounced in tasks such as simple reaction time, which repeat identical trial demands (Gilden, 2001). Apparently, correlated noise can be observed in all appropriately measured laboratory performances.

SELF-ORGANIZED CRITICALITY

Pink noise is a characteristic pattern of correlated noise associated with interaction-dominant dynamics and states of self-organized criticality. *Self-organization* entails a capacity to move between different, ordered, dynamic states—between qualitatively different patterns of behavior (Nicolis, 1989). *Criticality* refers to the balance among constraints that yields one or another ordered state. At or near a critical point, active competing constraints can be "forcefully" present at the same time in the same system. Near a critical point, mutually inconsistent constraints are poised together as potential constraints. The "pull" of these constraints extends across the entire system through interactions among neighboring processes. "The system becomes critical in the sense that all members of the system influence each other" (Jensen, 1998. p. 3). The presence of the pink noise pattern justifies serious consideration of this hypothesis.

The appeal of *self-organized criticality* is that systems near critical points are poised to access all potential behavioral trajectories (within the boundary conditions). Thus, near a critical point, the system is exquisitely context sensitive. The intention to perform speeded word naming, for example, positions the body as a word naming device near a critical point, which makes available a large set of mutually exclusive articulatory trajectories. Perception of the target word, with its entailed cognitive constraints, further restricts the set of potential trajectories. Over time, mutually consistent constraints combine to prune the set and exclude those trajectories that bear only superficial resemblance to the target pronunciation (Van Orden & Goldinger, 1994; Van Orden, Pennington, & Stone, 1990; cf. Kello & Plaut, 2000).

Protracted "cognitive pruning" of action trajectories implies that cognitive constraints are continually available to—are vertically coupled to—"peripheral" control processes of motor coordination (within the boundaries specified by intentional contents and other control processes on longer timescales). This hypothesis is supported by a growing family of experiments in which "central" constraints (attendant on cognitive factors) are available to peripheral control processes. Cognitive constraints are subtly reflected in the actual kinematics of motor trajectories (Abrams & Balota, 1991; Balota & Abrams, 1995; Gentilucci, Benuzzi, Bertolani, Daprati, & Gangitano, 2000; Zelinsky & Murphy, 2000). Pruning, itself, resembles simulated annealing (Shaw & Turvey, 1999; cf. Smolensky, 1986). Vertical coupling of embodied constraints simultaneously takes into account well-tuned cognitive constraints (e.g., learned relations between spellings and pronunciations), the current status of intentional contents, and other embodied constraints (the current status of articulatory muscles, breath, heartbeat, neural fluctuations, and so on) that are all implicated in each unique pronunciation trajectory. Over time, all pronunciations that fail to satisfy converging constraints are pruned from the potential set, which yields a globally coherent, locally efficient, articulatory trajectory (cf. Shaw, Kadar, & Kinsella-Shaw, 1994; Shaw, Kugler, & Kinsella-Shaw, 1990).

We just described the intentional basis for speeded word naming—an *intentional automatic performance* in conventional terms. But what about *autonomous automatic processing* as in the Stroop effect? Instructions in the Stroop procedure emerge as directed intentional contents that restrict behavior to ink-color naming—intentional contents that constrain a human body to become an ink-color naming device. This sets up a potential set of color-name articulatory trajectories, a necessary backdrop for the Stroop effect. Perception of ink color provides additional constraints that, with converging constraints, prune the potential set to an appropriate, globally coherent trajectory—a color-name pronunciation. However, if the colored ink is arranged in a shape that spells a color name, then cognitive constraints entailed by the color word come to bear in pruning, which may reinforce (speed up) or interfere with (slow down) pruning of extraneous trajectories.

If laboratory performances self-organize, then intentional contents are causally intertwined with learned constraints in so-called automatic performances. Moreover, intentional contents have an essential a priori function; they must emerge before there is any possibility of word naming or Stroop phenomena. We hope these examples illustrate how central the problem of intentionality is to laboratory observations of human performance. Any credible research program should begin with a plausible story of how laboratory protocols yield cooperative performances—a plausible story about intentional contents and self-control.

SUMMARY

This article has described the core assumptions of two research programs as they are spelled out in structural hierarchy theory and control hierarchy theory. By core assumptions we mean something close to what Lakatos (1970) called *negative heuristics:* defining assumptions that a research program must hold onto at all costs. To let go of a core assumption is to become a different research program. A successful research program will accrue empirical support for its core assumptions, which may stabilize research efforts around those assumptions. The inherent pattern of variability in behavioral measures could supply this kind of empirical support (cf. K. M. Newell & Slifkin, 1998; Riley & Turvey, in press).

Both research programs were described as to whether they may accommodate intentionality—arguably the first question of psychology. For example: Am I an automaton, or am I an intentional being? Is my apparently intentional act simply the end product of billiard-ball causality, or could it attend on a capacity for self-control as in self-organization? Do I reduce to specialized devices of mind, or am I a coherent whole that creates of itself specialized devices as circumstances require? Do the morphologically reductive methods of linear statistical analysis or strategically reductive nonlinear methods have greater utility for understanding my behavior?

The two views that we have contrasted supplied answers to the previous questions and made explicit links among the answers. (We know of no third alternative that can equally supply linked assumptions from existential *head* to methodological *foot.*) Structural hierarchy theory answered the questions as follows: Cognitive systems are automata. Behavior reduces to specialized component devices. Behavior can be viewed as the end product of linked efficient causes, and the methods of linear analysis should suffice to discover mental components as component effects. It is easy to see why research efforts grounded in the assumptions of structural hierarchy theory inevitably discover automata. Automatic behavior is the only kind of behavior that structural hierarchy theory acknowledges. But the core assumptions of vertical separation and loose horizontal coupling have yet to be corroborated. Moreover, correlated noise brings into question the basic premise of structural hierarchy theory, that mediating states can be individuated (Van Orden, Jansen op de Haar, & Bosman, 1997).

Correlated noise may imply a self-organizing system, which warrants research efforts that may take into account this possibility. Efforts to understand cognitive performances could pattern themselves after, and build on, previous efforts to understand motor coordination in terms of self-organization. Among other things, such research could focus on qualitative changes in cognitive performance to characterize, and motivate empirically, the relevant control parameters (e.g., Van Orden, Holden, Podgornik, & Aitchison, 1999). Of course this is not without its difficulties. Nonlinear methods can be challenging in their own right. Efforts may be rewarded, however. They may pay off in a plausible theory of self-control.

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APPENDIX

A dispersion analysis yields the fractal dimension of a trial series. The fractal dimension gauges the change in variability attendant on changing sample sizes. It may indicate whether variability converges fast enough, as sample sizes increase, to yield stable population parameters. If not, then the process that produced the variability is scale free—it has no characteristic "quantity" of variability. This appendix includes some guidelines for computing the fractal dimension of a trial series and a description of the specific analysis of the simple reaction time trial series portrayed in Figure 1a.

There are several ways to compute fractal dimension, but *dispersion* techniques are more accurate than other methods (Bassingthwaighte et al., 1994; Caccia, Percival, Cannon, Raymond, & Bassingthwaighte, 1997; Eke et al., 2000). Also, dispersion statistics are computed using means and standard deviations—familiar statistical constructs. To highlight the relation between these techniques and basic statistical theory, we adapted the usual technique of *relative dispersion analysis* to use normalized data instead of raw data. Relative dispersion analyses typically use the relative dispersion statistic, which is expressed in terms of a ratio of the standard deviation and the mean, that is, $RD = SD/M$ (see Bassingthwaighte et al., 1994). Using normalized data yields dispersion measurements in units of the standard error of the mean.

Begin with an experiment that may leave at least 1,024 observations after outliers, and so forth, are removed. These techniques can be applied to shorter data series, but, all other things being equal, fractal dimension estimates become more variable as progressively shorter data series are used (Cannon, Percival, Caccia, Raymond, & Bassingthwaighte, 1997). In addition, the measurements should be collected together as a continuous trial series. A "lined up" series of measurements, which were actually collected across different experimental sessions, distorts the timescale, and a fractal dimension analysis may not accurately characterize the temporal structure of the series. The data in Figure 1 came from a procedure that presented 1,100 simple reaction time trials, which included a healthy 76-trial buffer.

Response time tasks usually yield some extremely long (or short) response times. Regardless of whether these outliers result from equipment problems or represent legitimate measurements, they may distort the outcome of the fractal dimension analysis. For the illustrated analysis, we removed simple reaction times greater than 1,000 msec, then computed the series mean and standard deviation, and removed times that fell beyond ± 3 standard deviations from the trial series mean. If more than 1,024 measurements remain after trimming, then eliminate initial transients by truncating enough of the early trials to leave 1,024 observations.

Trial series that display self-similar fluctuations may be expected to display nonstationary drift at all scales. It can be difficult to distinguish a nested, fractal pattern of long-range fluctuations from long-range trends (Hausdorff et al., 1996), and long-range trends may bias estimates of fractal dimension. They may even overwhelm the fractal dimension analysis, yielding spurious fractal dimension statistics (Caccia et al., 1997; Hausdorff et al., 1996). Consequently, it is prudent to remove linear and quadratic trends (at least) before conducting the analysis. As a general rule, if the trial series has fractal structure, progressively more liberal detrending procedures will not dramatically change the fractal dimension estimate (cf. Hausdorff et al., 1996).

In the present example, the fractal dimension estimate was essentially the same whether only linear trends were removed or trends were removed up to a quartic. That being the case, we removed linear and quadratic trends. After that, the trial series was normalized leaving the measurements in units of standard deviation with a mean of 0 and a standard deviation of 1. When normalizing the series, and measuring dispersion in the subsequent steps, compute the standard deviation using the *population* formula (i.e., use n, the number of data points, in the calculation, rather than the usual bias-corrected $n - 1$).

Fractal dimension is calculated as follows: Construct a table, such as Table A1. The standard deviation of the series ($SD = 1$) estimates the overall dispersion of the series. Begin the table by recording a 1 in both the points-per-bin column and the dispersion column. Essentially, this treats the standard deviation ($SD = 1$) as a population parameter, and for this initial step, n also equals 1.

In the next step, group adjacent pairs of data points into two-point bins. Compute the average of the two points for each bin. The resulting 512 means becomes the new sample of data. Compute the standard deviation for this new sample. Enter a 2 in the first column of the table (two points were averaged to get each mean) and next to it, in the column labeled *Standardized Dispersion,* enter the standard deviation of the new sample.

Repeat the previous step until only two data points remain. The second iteration should yield 256 bins of size 4, the third iteration yields 128 bins of size 8, and so on, until there are only two bins—one containing the first half of the original trial series and one containing the last half. At each step, enter the number of points in each bin, and the standard deviation of the sample means.

Next, plot *Bin Size* and *Standardized Dispersion* against each other on log scales, as illustrated in Figure 2 (bases other than Base 10 will also work). Typically, the last few dispersion measurements, corresponding to the largest bin sizes, are excluded at this point (Cannon et al., 1997). Excluded points in Figure 2 appear as open circles corresponding to the larger bin sizes; the dispersion statistic for the

TABLE A1
Values That Come From the Iterative Procedure Used to Calculate the Fractal Dimension of the Trial Series Portrayed in Figure 1

Bin Size	*Standardized Dispersion*	*Log 10 Bin Size*	*Log 10 Standardized Dispersion*
1	1.0	0.0	0.0
2	0.84	0.30	–0.07
4	0.71	0.60	–0.15
8	0.58	0.90	–0.24
16	0.48	1.20	–0.32
32	0.36	1.51	–0.44
64	0.29	1.81	–0.54
128	0.19	2.11	–0.72
256	0.14	2.41	–0.85
512	0.05	2.17	–1.30

Note. Bin size is simply the number of points per bin at each iteration of the procedure. The underlined values printed in the two rightmost columns correspond to the filled circles of the graph in Figure 2; the remaining values in these rightmost columns correspond to open circles.

largest 512-point bins fell outside the axis limits and does not appear on the plot in Figure 2. The large bin sizes are so close to the size of the full data set that their variability estimates do not differ appreciably. Natural fractals are "truncated" by their finite range of scales, so the linear relation breaks down for the largest bin sizes (or sometimes for the smallest, or both). In the standardized series, they approach zero (and negative infinity when the log transformation is performed) and bias the slope of the regression line (for additional refinements of this technique, especially for shorter data sets, see Caccia et al., 1997).

If a linear relation exists between bin size and the standardized dispersion statistic (on log-log scales), then the trial series may be a simple fractal. The illustrated linear relation is a power-law scaling relation. The slope of the regression line is –.30, and the fractal dimension is 1.30, given by subtracting the slope from 1.