

Interdependence of Form and Function in Cognitive Systems Explains Perception of Printed Words

Guy C. Van Orden and Stephen D. Goldinger

Perception is described within a complex systems framework that includes several constructs: resonance, attractors, subsymbols, and design principles. This framework was anticipated in J. J. Gibson's ecological approach (M. T. Turvey & C. Carello, 1981), but it is extended to cognitive phenomena by assuming experiential realism instead of ecological realism. The framework is applied in this article to explain phonologic mediation in reading and a complex array of published naming and lexical decision data. The full account requires only two design principles: covariant learning and self-consistency. Nonetheless, it organizes and explains a vast empirical literature on printed word perception.

William James's (1890/1950) *stream of consciousness* may prove a prescient metaphor for cognitive phenomena. The dynamics of turbulent streams is one of several complex systems' metaphors shaping theory in psychology. Cognitive scientists have recently applied such metaphors to the complex stream of human behavior, experimentally induced or spontaneous. In this article, we are concerned primarily with human performance attendant on perception of printed words; the basis for our analogy to complex systems is recurrent feedback. There is a vast literature on word perception, rich in empirical constraints and detailed theory. Several recurrent feedback models of word perception have recently been developed, all embodying nonlinear dynamic systems theory—the mathematics of complex dynamic phenomena (Abraham, Abraham, & Shaw, 1991). Examples include McClelland and Rumelhart's (1981) interactive activation model of letter and word perception (see also Grainger & Jacobs, 1994a), Grossberg and Stone's (1986) account of recognition and recall, Kawamoto's (1988, 1993, in press; Kawamoto, Farrar, & Kello, 1994) model of naming and lexical ambiguity resolution, and Jacobs and Grainger's (1992; Grainger & Jacobs, 1994b) model of visual word recognition for lexical decisions. Less effort has been expended, however, toward exploring

the entailments of dynamic systems theory and its implications for models in psychology. In this article, we discuss these entailments as we explain perception of printed words.

Feedback processes were first introduced by Newton and Leibniz as dynamic laws that describe the unfolding of physical systems. They recognized that measures of a moon's position and velocity at one moment serve as input values for an equation that yields new values at the next moment. To predict a moon's trajectory through space becomes a simple matter of feeding back a model's output values as input values and tracking the path of successive outcomes. Such lawful feedback behavior is deterministic and predictable. Most contemporary models of natural systems, however, are far less predictable. Typically, the smallest mismeasurement of a system is magnified in the model by recurrent feedback; hence, a fully deterministic model can yield apparently arbitrary behavior (Lorenz, 1963). This distinction between deterministic, predictable systems and deterministic, unpredictable systems is correlated with the distinction between linear and nonlinear systems (Peitgen, Jürgens, & Saupe, 1992).

The first 300 years of science are largely a history of systems that can be modeled as having components that produce their effects in predictable linear combinations. This systemic view has typically been imposed on cognition as well, including theories of word perception (e.g., Massaro & Cohen, 1994). Enthusiasm for linear analysis has led some to argue that only componential systems, exhibiting "regular" behaviors, can be analyzed (e.g., Fodor, 1983). Regular behavior is, somewhat circularly, assumed to be the true signal of a system's underlying deterministic and predictable character. Ostensibly arbitrary or irregular behavior is considered "noise," obscuring the "signals" of regular phenomena (e.g., Chomsky, 1965; Moses & Flavell, 1990). The empirical challenge is couched as the discovery of regular behaviors against a noisy background of random flux. Given the assumption of linear determinism, observation of a behavioral regularity in cog-

Guy C. Van Orden and Stephen D. Goldinger, Cognitive Systems Group, Department of Psychology, Arizona State University.

Preparation of this article was funded by National Institutes of Health FIRST Award CMS 5 R29 NS26247-04 to Guy C. Van Orden.

We thank Claudia Van Orden, who was our host while we drafted the penultimate version of this article. We thank Tony Gerard and Marian Jansen op de Haar for comments on previous versions. We are especially grateful to Ken Paap for his insightful and detailed review of this article and to Art Jacobs for helpful conversations about this research. Many ideas developed here originated in our ongoing collaboration with Greg Stone.

Correspondence concerning this article should be addressed to Guy C. Van Orden, Cognitive Systems Group, Department of Psychology, Box 871104, Arizona State University, Tempe, Arizona 85287-1104.

nitive systems is tantamount to discovering an independent component or aspect of mind.

Componential linear analysis is also the basis for many statistics used in psychology. We typically fit data to a linear model, such as in analysis of variance (ANOVA), and assume that significant fits reveal separate (but possibly interacting) factors in behavior. These independent factors are assumed to originate in mediating representations and processes that stand between proximal stimuli and performance (see Mandler, 1985). The overarching goal has been to compile a complete catalog of mediating structures and processes—the architecture of cognition—that generates all human behavior (with a tolerable degree of error). Heated theoretical debate occurs because different scientists find different components or combinatorial laws in their data, with the differences to be resolved by more careful measurements or more thorough examination of the full range of the potentially causal variables.

Linear analyses are, of course, best suited for phenomena in which underlying functional components combine their effects in a strictly linear or quasilinear fashion. When systems are not strictly decomposable, exclusively linear analyses may yield an overly complex picture. The number of entries in our theoretical catalog will grow at roughly the same rate as the number of apparently independent sources of variance that we discover in data, and debates concerning the components of the system will prove irresolvable. Concerning the latter point, Uttal (1990) has marshaled persuasive arguments that converge on a common conclusion: Componential analyses of cognitive systems are, in principle, indeterminate. Proponents of componential analyses may find Uttal's summation depressing: "... no formal model is verifiable, validatable, or even testable with regard to internal mechanisms" (Uttal, 1990, p. 201).

We agree with Uttal (1990); the architecture of cognition is not transparent to componential analysis. Nevertheless, linear componential analysis is an indispensable heuristic for deriving a first-order description of behavior (cf. Bechtel & Richardson, 1993). However, it fails as an end point of explanation for cognitive systems because it fails to reduce the complexity of data. It often appears that linear analysis fully degenerates into case-by-case explanation, with little hope of recovery (for a related discussion, see Mandler, 1985, p. 22). We propose that simpler, higher order accounts may be derived from extant, first-order, linear descriptions. We drop the axiomatic assumption that cognitive systems must be composed of independent operators (Stone & Van Orden, 1993). Instead of being mediated by linear combinations of component functions, behavior may emerge from strongly nonlinear systems. Nonlinear systems can be quite simple, yet produce lawful, complex behaviors (Rumelhart & McClelland, 1986b), so they are promising metaphors for lawful, complex cognitive behaviors, including perception.

What follows is our attempt to describe perception of printed words as a fully interdependent, nonlinear, dynamic system. We do not present a model of word perception per-

se.¹ Instead, we outline a theoretical framework, derived from dynamic systems theory, within which models can be constructed. The next sections introduce the terms of our analysis: resonance, attractors, subsymbols, and design principles (see also Stone & Van Orden, 1994). Once the basic framework is in place, we apply it to perception of printed words. Our goals are to account for a wide range of data using a minimal set of design principles and, perhaps more importantly, to illustrate an alternative style of explanation in psychology. First, we address a fairly specific problem—phonologic mediation in reading (see also Van Orden & Goldfinger, 1994). Second, we analyze performance from naming and lexical decision experiments—the standard laboratory tasks in the vast literature on word perception.

Complex Systems Framework

Resonance

Imagine a fictitiously simple neural system that perceives printed words. This system comprises a family of neurons affiliated with vision and a family of neurons affiliated with language. Each vision neuron is potentially connected to every language neuron and each language neuron is potentially connected back to every vision neuron. Now imagine a specific pattern of activation across the vision neurons, due to the presentation of a printed word. This visual pattern feeds forward through the matrix of "synaptic" connections, creating a pattern of activation across the linguistic neurons. The linguistic neurons, in turn, feed activation back through a top-down matrix of connections, transforming the linguistic pattern back into a visual pattern. Wherever the fed-back pattern matches the initial visual pattern, top-down activation conserves bottom-up activation. Consequently, the visual pattern conserves its capacity to re-activate matching linguistic patterns that, in turn, re-activate the visual pattern, and so on. Within limits, this resonance is self-perpetuating and binds the respective patterns of activation into a coherent whole. The visual pattern initiating such interactive activation need not perfectly match its resultant feedback

¹ Farrar and Van Orden (1994) used the dynamic framework described in this article as a blueprint in constructing a simulation of printed word naming. The functioning dynamic system is a scaled-down "toy" simulation, in the sense of the number of computations performed. The main compromise was the small pool of words that the model learned, relative to large-scale models (e.g., Coltheart, Curtis, Atkins, & Haller, 1993; Plaut & McClelland, 1993; Seidenberg & McClelland, 1989). Farrar and Van Orden trained the model using a Hebbian-type learning algorithm and then observed the model's naming behavior. The network correctly mimics theoretically important qualities of naming performance by skilled readers and acquired dyslexics. Specifically, this recurrent "neural" network exhibited important patterns of intact, skilled, naming performance (e.g., a Frequency × Regularity interaction), and then, subsequent to respective simulated lesions, the model produced deep dyslexics' semantic errors (e.g., BUSH named as TREE) and surface dyslexics' regularization errors (e.g., PINT named to rhyme with MINT).

for resonance to occur. Combined cooperation between "levels" and competition within "levels" smoothes out small mismatches, but large mismatches prohibit resonance (Grossberg & Stone, 1986).² In a strongly nonlinear system, initial inputs are subject to successive nonlinear transformations, producing a new output, which then transforms the original input. Consequently, input and output become fully and irreducibly interdependent in the course of recurrent dynamics (cf. Turvey & Carello, 1981).

Of course, this simple, "vanilla," neural network is only for exposition. We find it helpful to think of words' features as neurons and their statistical interconnections as synapses. In its explanatory power, however, the analogy between cognitive and neural systems is only slightly stronger than analogies we might draw between cognitive systems and weather or turbulent flow. Coherent recurrent feedback can be used to explain coherent dynamic structure in physical, chemical, biological, cognitive, and social systems (Abraham et al., 1991; Grossberg, 1980; Nowak, Szamrej, & Latané, 1990; Prigogine & Stengers, 1984), all of which are not equally reducible to neural accounts. Word perception may just as well be conceived in cognitive terms, as follows: When a pattern of activation across visual features (however conceived) activates a pattern of linguistic features (however conceived), the linguistic features, in turn, feed activation back to visual features. If the stimulus-driven visual pattern adequately matches this fed-back pattern, the cycle is self-perpetuating. The visual features coalesce with the linguistic features in a coherent dynamic whole—a *resonance*.

We are certainly not the first to use the resonance metaphor as a psychological construct. From the mid-1960s onward, J. J. Gibson used the term *resonance* as a metaphor to explain how stimulus information specifies affordances (Lombardo, 1987) and, by the 1980s, that term had entered the vocabulary of cognitive scientists such as Grossberg (1980) and Shepard (1984). Grossberg's (1980) article in *Psychological Review* was our introduction to the concept of resonance, and the ongoing work of Grossberg and his colleagues constrains our interpretation of this construct (e.g., Grossberg & Stone, 1986; Stone & Van Orden, 1989, 1993, 1994; Van Orden, Pennington, & Stone, 1990). Grossberg's research program is aimed, however, at reducing cognitive constructs to neural realities—where we see a neural metaphor, he sees neurons. Shepard's (1984) discussion of resonance focuses on the relation between external stimulus forms and internal representations of those forms. This use of the term *resonance* seems to entail metaphysical realism, which maintains a principled line between perception and an external set of perception-independent objects (e.g., see Putnam, 1990). We do not use resonance in this sense of representing an external reality. Resonance in our framework occurs directly between stimulus forms and the functions they serve for perceivers.

Our view of resonance entails *experiential realism*, which we hope to clarify in a comparison with Gibson's (1979/1986) *ecological realism*. A resonance in which form and function are interdependent is reminiscent of Gibson's description of affordances (i.e., stimulus invariants specifying

functional affordances are directly perceived by a functionally oriented organism). Gibson did not formalize the term *resonance* in his theory of affordances. However, Lombardo (1987) gleaned a few defining characteristics from Gibson (1971): "It is holistic, continuous, active, selective, ecological, involving adjustment and equilibration, and circular rather than unidirectional" (Lombardo, 1987, p. 303). With respect to this shopping list, we agree that resonance is holistic, continuous, active, selective, involving adjustment and equilibration, and circular rather than unidirectional. However, it is not ecological, if this term strictly implies unmediated perception (e.g., Fowler, 1989; Turvey & Carello, 1981). Once we accept that stimulus function may specify stimulus form, we must also accept that perceptual events have an experiential, not ecological, basis.

A basic premise of ecological psychology is that stimulus form specifies function, as when a surface affords support. This is superficially true in language as well; the written or spoken forms of words specify (or at least constrain) their linguistic function. However, the functions of language also specify perceived form. Consider an example from speech perception. When listening to speech in an unfamiliar language, people inevitably wonder why speakers "talk so fast." All languages are spoken at equivalent rates. In a familiar language, however, we perceive breaks between words (although no physical breaks exist), which "slows down" perception. Unfamiliar languages sound fast because the listener lacks functional constraints to segment continuous speech. When a listener can perceive the linguistic function of speech, there is a qualitative change in perceived form. This example illustrates why speech perception resists explanation in terms of affordances (see Goldinger, Pisoni, & Luce, in press).

Our claim here is not a rejection of the ecological approach; practitioners of that approach provided theoretical discussion that anticipated much of the present framework (see Turvey & Carello, 1981). Neither is our claim a retreat into relativism; we do not believe that individuals manufacture functional constraints at will. For example, just as being a corporeal body precludes perception of a brick wall as a medium to walk through, being a French speaker precludes perception of French as "foreign speech." We merely dispense with objective ecological realism in favor of experiential (or internal) realism (Johnson, 1987; Lakoff, 1987; Putnam, 1981, 1990). Reliable functional constraints resonate with reliable stimulus forms, and reality is emergent in the content of human experience.

We do claim, however, that "unmediated" phenomena, more typically considered in ecological psychology, are important special cases that may be nested within a broader

² This match/mismatch function accomplishes verification (cf. Becker, 1976; Paap, Newsome, McDonald, & Schvaneveldt, 1982; Van Orden, 1987). Unlike traditional accounts, however, it does not require a record of an initial sensory representation. Perception (including verification) fundamentally changes the sensory record; countless psychological dimensions (including stimulus name, meaning, etc.) are incorporated into a percept.

cognitive systems framework. Perception will appear unmediated when (mostly) invariant stimulus information is strongly correlated with functional features (Bechtel & Abrahamson, 1991). When stimulus information is invariant, forms are not ambiguous. Gibson emphasized, almost exclusively, perceptual events specified by invariant stimulus information, that is, veridical perception (Gibson, 1979/1986). This pragmatic emphasis strategically postponed analysis of problems related to ambiguous or arbitrary stimulus forms. This strategy allowed him to emphasize the environmental side of the organism–environment dynamic. We, on the other hand, cannot escape the fact that a printed word (or spoken word) has an arbitrary form that is only realized perceptually through its linguistic function. We are forced to put greater emphasis on the organism side of the organism–environment dynamic. In particular, we cannot escape the problem of resolving ambiguity of function. To our knowledge, Gibson did not fully confront this problem because it is much less conspicuous in the psychology of invariant forms.

If perception entails full reciprocity between environment and organism, then perception must resolve ambiguity of both form and function. In the extreme, unresolved ambiguity of either form or function will reverberate and undermine veridical perception. In a less extreme scenario, failure to disambiguate function leaves the perceiver stuck between affordances, unable to act. Like Gibson (1979/1986), we imagine that perception is continuous with action. To us, this means active competing functions reciprocally specify perceived form. Consequently, our use of the term *resonance* is closer to Varela, Thompson, and Rosch's (1991) use of the term *enaction* than to Gibson's use of *affordance*. In their words, *enaction* is “[a] history of structural coupling that brings forth a world” (pp. 206–207). As we illustrate in the second half of this article, the topology of dynamics is largely a product of fine-grain associative learning (i.e., a “history of structural coupling”), and in this section we have argued that resonance entails experiential realism (i.e., “structural coupling that brings forth a world”).

Attractors

Resonance is a construct of dynamic systems theory, and dynamic systems theory provides additional tools for describing the behavior of complex systems. For example, correlated forms and functions may be described in a topology of attractors across a state space (Abraham et al., 1991; Killeen, 1989, 1992). A *state space* (sometimes called a *phase space*) comprises all possible states that a system may occupy. An example of a state space for word perception may be distributed along visual and linguistic dimensions, corresponding to the visual and linguistic features (broadly conceived) of printed words. Each feature is merely a single descriptive dimension of a high-dimensional space. Points in this space are unique combinations of visual and linguistic features. Temporal properties of performance are mimicked in the time needed to move between points in the state space (cf. Killeen, 1989). The dynamic leading to resonance

may be described as movement between a point corresponding to initial conditions and a point attractor.

Word perception begins with the presentation of a printed word, which activates visual dimensions of the state space. Feedforward activation, in turn, activates linguistic dimensions. This initial combination of visual and linguistic dimensions composes the initial conditions of word perception. Initial conditions include both appropriate and inappropriate feature dimensions. For example, the linguistic dimensions of a printed word include phonologic dimensions. Concerning these phonologic dimensions, *_INT* is pronounced differently in *PINT* and *MINT*, and so initial conditions of *PINT* will include some phonologic features of *MINT* (Kawamoto, 1993, in press; Kawamoto & Zemblidge, 1992; Van Orden et al., 1990). More generally, the initial conditions of a perceptual event include all functional dimensions previously associated to a stimulus form, each activated in proportion to its statistical association with stimulus elements. Following this initial state, cooperative-competitive dynamics begin. In typical cooperative-competitive dynamics, appropriate dimensions are fully activated and inappropriate dimensions are inhibited. Activation of a feature is movement toward a point that includes that dimension; competitive inhibition of a feature is movement toward a point that lacks that dimension. Such “clean-up” dynamics produce a trajectory from the initial conditions to an attractor point—the point comprising the feature dimensions that eventually come into resonance.

Attractors develop as a consequence of learning.³ Each attractor in state space is bounded by a separatrix, a (high-dimensional) boundary that circumscribes an attractor basin. Within the attractor basin, dynamics move encodings toward the respective attractor point; beyond the separatrix, encodings fall in the basin of some other attractor (cf. Maddox & Ashby's, 1993, discussion of decision boundaries in perceptual categorization). Word perception experiments typically collect response time and accuracy data. With regard to the former, the distance traveled in an attractor basin between the initial encoding and the attractor point is positively correlated with response time (Kawamoto, 1993, in press; Kawamoto & Kitzis, 1991; Kawamoto & Zemblidge, 1992; Plaut & McClelland, 1993; Seidenberg & McClelland, 1989; Van Orden, 1987; Van Orden et al., 1990). With regard to the latter, the attractor point usually comprises visual and linguistic features consonant with a correct response. On occasion, however, errors occur, as when *PINT* is mispronounced to rhyme with *MINT* in a naming task or when *ROWS* is misidentified as *A FLOWER* in a categorization task. Such errors may be thought of as encodings that fall into false-positive attractor

³ Evolutionary history may also shape form–function attractor topologies across successive life spans of many individuals (Killeen, 1989, 1992; Kohonen, 1988; Rumelhart & McClelland, 1986b; Shepard, 1989). For example, functional environmental regularities may be “selected” by evolutionary processes and show themselves behaviorally in form–function attractors that emerge reliably in maturation. Such regularities may include aspects of phonology.

basins, typically basins that adjoin the correct attractor basin (Hinton & Shallice, 1991; Kawamoto, 1993, in press; Kawamoto & Kitzis, 1991; Kawamoto & Zemblidge, 1992; Plaut & Shallice, in press; Van Orden et al., 1990; Van Orden, Pennington, & Stone, 1994). Errors often resemble correct responses because adjoining attractor basins share visual-linguistic dimensions.

As we attempt to illustrate in the second half of this article, relative distances between attractors, and between initial encodings and attractors, may be estimated from the qualities of empirical phenomena. We are restricted to qualitative analysis because the manipulated ranges of independent variables and the observed ranges of dependent variables in psychological experiments often lack meaningful interval properties. For example, when we manipulate the relatedness of meaning between a "prime" and a "target"—as when DOCTOR is chosen as a related prime for NURSE versus an unrelated prime such as CHAIR—we manipulate the relationship "more than," but we do not know "by how much." Likewise, when we observe structured errors—as when PINT is pronounced to rhyme with MINT—we only know that the error is more similar to the correct response than if PINT had been pronounced to rhyme with JALAPEÑO. The precise interval relations along psychological dimensions, whether manipulated or observed, remain indeterminate.

At the heart of our argument is the following: With neither linear decomposability nor interval-scale quantification of psychological dimensions, we cannot deduce a set of elementary causal structures that underlie the performance of cognitive systems. We can, however, construct a hypothetical topology of the state space by reference to the topology of performance (i.e., the directions and relative magnitudes of reliable effects). For example, response times in naming experiments are typically faster than response times in lexical decision experiments. This result holds when both tasks include the same words and subjects are drawn from the same population (e.g., Forster & Chambers, 1973; Waters & Seidenberg, 1985), and when the same subjects complete both tasks and the respective stimulus sets are drawn from the same population (e.g., Llewellen, Goldinger, Pisoni, & Greene, 1993). Likewise, within each of these tasks, we can rank order performance to classes of word types (e.g., consistent vs. inconsistent words), or with respect to other independent variables (e.g., word frequency). Perhaps most importantly, we can track patterns of interaction among variables, strictly limiting the set of possible trajectories through the state space.

Subsymbols

The limits on mapping out a state space are closely related to limits on prediction. As we noted earlier, in strongly nonlinear systems, even minute differences in initial conditions may be amplified by feedback and result in gross qualitative changes in system performance (e.g., PINT pronounced to rhyme with MINT). Thus, the limits on specifying initial conditions also impose strict limits on our

capacity to predict system performance. Formal modeling, however, requires that initial conditions be made explicit. Consequently, we require pragmatic substitutes for complete specification of initial conditions that minimally impact system performance. We propose that patterns of activation across subsymbols may stand in for the initial conditions of cognitive systems. Subsymbols are discrete notations that "fix in place" the dimensions of a state space for purposes of modeling or illustration (cf. with the term *coordinative structures* in Turvey, 1977). For example, we often use letter and phoneme subsymbols in models and figures (Van Orden, 1987; Van Orden et al., 1990). In dynamic models, subsymbols are the nodes that interact in resonant dynamics.

Van Orden et al. (1990) proposed the following heuristic for choosing subsymbols in a model: (a) Use data to reveal the finest grain size of form–function correspondence (co-variation) that predicts the performance to be modeled. (b) Fix the grain size of subsymbols equal to, or finer than, the grain size of this correspondence. For example, in illustrations of word perception, we require a grain size of visual-linguistic correspondence that best accounts for performance in simple reading tasks. Our subsymbols might approximate letters, phonemes, and morphemes. These are the finest grain visual–phonologic–semantic correspondences that correlate with performance in typical reading tasks. However, we would require a finer grain size in more general models of perception or reading lest we fail to account for finer grain data patterns (Patterson, Seidenberg, & McClelland, 1989; Sanocki, 1987) or data patterns due to context-specific, "episodic" aspects of stimuli (cf. Goldinger, 1992; Jacoby, 1983; Jacoby & Hayman, 1987; Sanocki, 1987).

In the heuristic use of subsymbols required in this approach, we must avoid assigning any grain size of observed performance the privileged status of being more psychologically real (or fundamental) than some other grain size. Thus, we try to avoid debates as to whether "letters" or "bigrams" are more fundamental units of word perception. Of course, this merely extends Gibson's (1950, 1966) insight that there is no privileged grain size of physical reality. Just as the environment nests multiple grain sizes of form, embedding finer grain forms in more coarse-grain forms (Gibson, 1966), so too does performance nest multiple grain sizes of form–function correlation, embedding fine-grain functional correlations within coarse-grain correlations (Turvey & Carello, 1981; Turvey, Shaw, Reed, & Mace, 1981).

It is easy to confuse subsymbols with traditional symbolic representations. In models, both may appear as nodes that are activated in the course of processing, and they may have similar names (e.g., phonemes vs. phonologic subsymbols). However, the pragmatic "identities" of subsymbols have a purely narrative function in our approach, which sets strict limits on their interpretation. They should not acquire ad hoc "reality," nor should subsymbols, in and of themselves, be attributed any causal or explanatory properties that are independent of the resonant dynamics in which they participate.

In a subsymbolic model, the explanatory relation is between behavior and emergent dynamic structures (resonances). Unlike componential physical symbol system models, where each potential behavior is made explicit in underlying rules and representations, the explanatory set of possible resonances is only implicit in the underlying architecture. Additionally, identical patterns of behavior may emerge from an unending variety of architectures, even if they include different subsymbols (or even symbolic representations). Any model that self-organizes through recurrent feedback can reproduce its performance profile with different arrays of subsymbols. For example, it is trivial to pick subsymbols of a finer grain size, but a model's performance will be identical so long as the patterns of correlations among the previous coarse-grain subsymbols are preserved (Van Orden et al., 1990). As a consequence, the choice of a model's subsymbols is, to a large degree, arbitrary.

Beyond avoiding irresolvable debates, maintaining the narrative function of subsymbols is important in another way—it protects the possibility that we may develop a truly general theory of perception. Consider cross-language comparisons: Many theories of word perception rely on their representational assumptions to account for relevant data. A common and frustrating experience, however, is to have a theory "falsified" by refutation of its specific representations. For example, we can easily verify the "psychological reality" of letters in English, so we may incorporate letter units in a model of reading. Inevitably, we are reminded that the model cannot account for the reading of Chinese characters, so we require a new set of representations for the Chinese model. (Indeed, countless conversations among psycholinguists have ended shortly after someone said, "Well, that's true in *English*. But in Icelandic/Arabic/Urdu . . .") Languages differ not only in their apparent orthographic and phonologic units, but in stress patterns, optimal parsing strategies, and so on. Beyond such surface distinctions, evidence for the Whorfian hypothesis (e.g., Hunt & Agnoli, 1991) suggests that basic semantic representations differ across languages as well (cf. Lakoff, 1987). Hence, although we assume narrative notations convenient to describing the behavior of readers of English, the explanatory power of the approach lies in the dynamics of the resonance process.

The narrative function of a model's subsymbols shares a common denominator with the widely accepted conclusion that data are perspective laden. (Miyake, 1986, illustrates this conclusion beautifully in a study of subjects' attempts to explain how a sewing machine works.) For example, word perception may be studied in a naming trial, yielding two data points corresponding to accuracy and response time, but word perception is only partly correlated with naming, which in turn, is only partly correlated with accuracy and response time. The data entail a narrow perspective, circumscribed by pretheoretical conventions of method and analysis. Likewise, subsymbol identities originate in pretheoretical perspectives; they derive from a priori knowledge (e.g., visual subsymbols for a model of visual word identification), categories of independent variables (e.g., phonologic and semantic subsymbols), appeals to the au-

thority of other analyses (e.g., subsymbols corresponding to syntactic values or image schemas), and so on. Subsymbols are fully and explicitly perspective-laden; they have no absolute properties. Even their assignment to form and function is a pragmatic distinction. With respect to printed word perception, visual subsymbols are features of form, and phonologic subsymbols are features of function. However, to explain performance attendant on speech perception (Dijkstra, Frauenfelder, & Schreuder, 1993), form and function would realign accordingly. The pragmatic identities of subsymbols anchor models' architectures in a coherent scientific narrative that is essential for a shared understanding of models.

Design Principles

Previously, we described a covariant learning hypothesis (Van Orden, 1987; Van Orden et al., 1990) that entails a design principle. The covariant learning hypothesis explains how a system is developmentally configured by tracking correlations of stimulus forms and their functions, and the specific consequences for performance. The design principle of covariant learning refers jointly to patterns in data and in the models' behavior (cf. van der Maas & Molenaar's, 1992, use of trajectories through control planes in their application of catastrophe theory to stagewise cognitive development). This design principle circumscribes the set of possible models that meet the criteria specified in the data. In the next section, we describe a self-consistency hypothesis that also entails a design principle. This self-consistency principle describes how covariance of forms and functions predicts performance of cognitive systems organized through recurrent feedback. Here, we briefly explain the relation of design principles to theory in psychology.

The most interesting adaptive dynamic models are strongly nonlinear. One must usually conduct simulations to discover the full complexity of their performance. However, broad performance principles can be induced by observing parallel performance across families of models. When these parallels in models' performance also parallel empirical performance, this relation is called a design principle. (Note that design principles reside in performance; they need not be explicit in a model's architecture. For a more detailed treatment of this issue, see Stone & Van Orden, 1994.) We believe induction of design principles promotes more general theoretical insights than strong-inference competitions between specific models. This does not devalue strong inference. It is informative to pit hypotheses against each other, including hypotheses corresponding to design principles. However, by shifting our theoretical emphasis to design principles, we acknowledge that identical performance profiles may arise from many architectures, including ostensibly different architectures (Dunn & Kirsner, 1988, 1989).

Figure 1 illustrates a complementary relation between induction of design principles and strong inference. The Sets **A** and **B** in the figure are the respective behaviors that

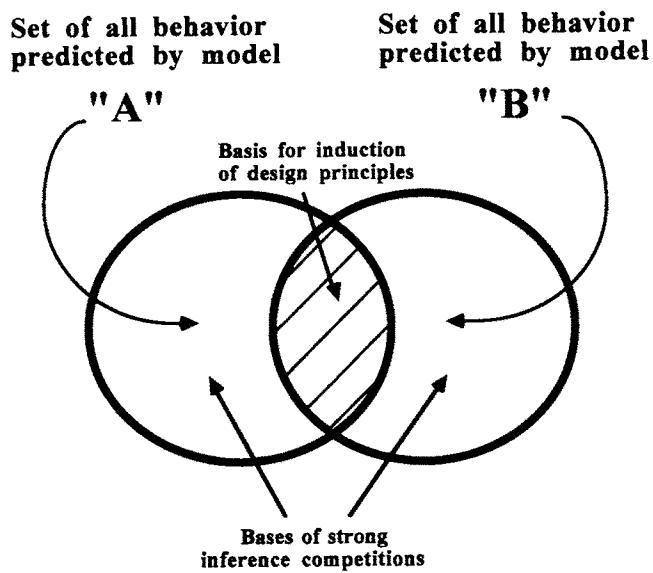


Figure 1. Sets A and B are the ranges of performance that can be observed of some Models A and B, respectively. The intersection of A and B specifies the range of performance common to both models. The complements of A and B may include contrasting predictions of Models A and B.

can be observed in Models A and B. In the induction of design principles, a theorist focuses on the intersection of A and B. Strong inference focuses on the subsets of A and B that complement this intersection. A theorist intent on comparing the models will search the complementary subsets for specific predictions that may be tested in critical experiments. This is a worthwhile enterprise, but its exclusive use is not without danger. For example, suppose we conduct an experiment that favors Model A. For models capable of complex behavior, an experiment samples only a minute region of the complement. We cannot know whether other points of contrast would have favored Model B. Thus, we may discard Model B prematurely. Also, an exclusive focus on strong inference would fail to explore the shared successes of models in the intersection of A and B.

A design principle is one outcome of seeking the source of common performance across models. Close examination may reveal *homologs*, such that models contain identical mechanisms, or *analog*s, wherein different mechanisms produce equivalent behavior. Homologs reduce to one model within the range of common performance. Analogs reveal a deeper relationship, a design principle, that may be abstracted from the particular instantiations. A design principle explains empirical phenomena, but the explanation arises with equal credibility from all models that respect the relevant data. For example, the common finding of frequency effects in word perception has been modeled through a variety of mechanisms. These include frequency-sensitive thresholds, resting activation levels, activation rates, search order, verification order, connection strengths, and time to resonance. Across models, these analogous mechanisms all track the desired behavior and thus allow

induction of a simple but important design principle: Response time is negatively correlated with word frequency. In a given model, we may use any mechanism that mimics frequency effects, although we prefer simple mechanisms that express additional, more complex design principles. Ideally, a set of models sharing a design principle may be recast in a canonical model that yields reliable predictions for the entire set (Stone & Van Orden, 1993).

A focus on design principles helps avoid premature falsification of an approach because a particular model taking that approach made wrong assumptions, convenient for the modeling but not central to or defining of the approach. For example, this mistake occurs when a particular model (simulation) is "falsified," but its failure derives from an isolable subset of mechanisms, arbitrary choices made for computational (analytic) convenience, or other peripheral considerations. Examples include the premature falsification of Rumelhart and McClelland's (1986a) approach to verb past-tense learning offered by Pinker and Prince (1988) or the premature falsification of Seidenberg and McClelland's (1989) approach to printed word naming, offered by Besner, Twilley, McCann, and Seergobin (1990; see also M. Coltheart et al., 1993). In both cases, it was later shown that the falsification applied only narrowly to particular assumptions and did not impugn the class of models that exhibit covariant learning (Plaut & McClelland, 1993; Plunkett & Marchman, 1991; Seidenberg, Plaut, Petersen, McClelland, & McRae, 1994).

Perhaps more important, a focus on design principles may avoid the converse of premature rejection, in which we commit to a model that is not unique in its explanatory qualities. No single mechanism can be proven as a necessary basis of human performance. At most, we may identify families of mechanisms that are sufficient to produce complex patterns of observed behavior. A focus on design principles acknowledges this limit and avoids false logics that are based on necessity. This focus also agrees with the practice of cognitive science as an historical science:

The test of adequacy of an historical science is its ability to provide a plausible account whereby a wide variety of complex phenomena could have been produced by the action of a small set of basic processes. In a mature historical science, the principles that summarize the action of basic processes are *sufficient* to account for complexity, but they cannot be shown to be necessary for its occurrence. (Donahue & Palmer, 1989, p. 400; emphasis in original)

Printed Word Perception

In the remainder of this article, we apply the constructs from the previous sections in an account of printed word perception. Our account is based on two design principles, covariant learning and self-consistency, that together describe the qualities of empirical findings across a vast literature (see also Van Orden et al., 1990). Next, we consider the initial conditions that follow the presentation of a word and the consequences for accounts of word perception.

Initial Conditions

Assume that presentation of a printed word initiates a massive spread of activation from visual features to linguistic features. For simplicity, we imagine this spread of activation in a model that includes visual, phonologic, and semantic subsymbols and their interconnections. We could unfold this interconnected network and lay it out as a vast, triangular sheet of nodes (see Figure 2) with visual subsymbols in one corner, phonologic subsymbols in a second corner, and semantic subsymbols in the third corner. Readers familiar with connectionist models of word identification will notice a resemblance between our triangle of interactive activation and the figures that illustrate those models (e.g., McClelland & Rumelhart, 1981; Seidenberg & McClelland, 1989).

Referring to Figure 2, stimulus presentation initiates a pocket of activation in the visual corner, which spreads simultaneously to the phonologic and semantic corners. (This initial spread of activation is indicated in the figure by bold arrows.) A discrete approximation (simulation) of this spread would be accomplished in one step: A visual vector is multiplied by a matrix that transforms it simultaneously into a phonologic-semantic (linguistic) vector. This first time-step ends with diffuse patterns of activation, including all phonologic and semantic subsymbols previously associated with active visual subsymbols. Take careful note of this initial state; the only apparent structure derives from the identities of the subsymbols. As we noted earlier, however, there is no behaviorally meaningful structure in the separate identities of these notations. This point is clarified by example: Consider the variation in visual features that make up a letter. Each "letter" of the alphabet connotes an intricate local topology of feature sets that share a family resemblance. "Letters" are not canonical entities; they are categories, with full natural variability. Of course, some feature combinations are more typical, as in common typefaces. However, instances of a letter can differ substantially, as the visual characteristics of letters differ between type fonts, when written in script, or when spelled out in the

shards of a shattered gin bottle. Canonical entities, such as letters or phonemes, are not explicit (or at least identifiable) in cognitive systems. Meaningful structure only emerges in resonance. After the initial spread of activation, cooperative-competitive dynamics begin among all subsymbol families, and coherent structures emerge as relatively stable feedback loops. Thus, high-level structures (even letters are considered high level), crudely approximated by our notational scheme, do not exist independent of interactive activation. A complex systems view emphasizes the emergence of cognitive structures through cooperative-competitive dynamics and thus reveals the purely narrative function of notations, such as "nodes," in models. A more fantastic notational simplification occurs in our separation of semantic subsymbols from visual and phonologic subsymbols. Semantic subsymbols are assumed to stand in for a vast range of sensorimotor ensembles that massively overlaps the dimensions of "visual" and "phonologic" dynamics (cf. semantic subsymbols to image schemas; Johnson, 1987; Lakoff, 1987).

Covariant Learning

The covariant learning hypothesis concerns the development of an attractor topology for word perception, in which visual forms come to shape, and be shaped by, their linguistic functions (Stone & Van Orden, 1994; Van Orden, 1987; Van Orden et al., 1990). This hypothesis demands a characteristic profile of development:

1. Forms and functions are associated on a stimulus-specific basis. Thus, early in development, performance is governed by relatively stimulus-specific attractors.
2. Eventually, rulelike performance emerges as the attractor topology is shaped by correlations across form-function pairs.
3. Finally, with sufficient experience of individual form-function relations, performance may converge on an asymptote.

Thus, effects of "irregularity" are diminished or eliminated for high-frequency form-function relations. This hypothesis has been applied to verb past-tense acquisition (MacWhinney & Leinbach, 1991; Plunkett & Marchman, 1991; Rumelhart & McClelland, 1986a), German definite-article acquisition (MacWhinney, Leinbach, Taraban, & McDonald, 1989), and the development of printed word perception (Plaut & McClelland, 1993; Seidenberg & McClelland, 1989; Van Orden, 1987; Van Orden et al., 1990).

When the same visual-linguistic correspondence is shared across a neighborhood of words, consistent cross talk will benefit performance. Consistent cross talk extracts correlations between forms and functions and across families of form-function pairs. In word naming, consistent cross talk is the source of many common effects, such as rule-strength effects and word frequency effects. Rule strength is estimated by a count of all words that share a particular grapheme-phoneme correspondence (e.g., B-/b/). Strong-rule words (e.g., *bask*) and pseudowords (e.g., *besk*), in which the "weakest rule" is a strong rule shared by very many words, are named faster and more accurately than

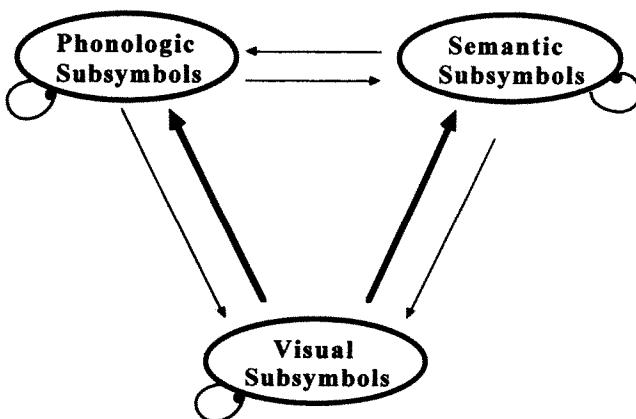


Figure 2. An interconnected network of subsymbols for modeling printed word perception.

weak-rule words (e.g., *fizz*) and pseudowords (e.g., *nozz*), in which the weakest rule is shared by few words (Rosson, 1985; Van Orden et al., 1994; see also Johnson & Venezky, 1976; Ryder & Pearson, 1980). Also, high-frequency words are named faster and more accurately than low-frequency words (Forster & Chambers, 1973). Figure 3 illustrates the source of these effects, as proposed in the covariant learning hypothesis. BE and BY share a relatively strong rule ($B \leftrightarrow b_1$), and BE is the more frequent word (in the figure).

In Figure 3a, a BE learning trial increases four pairs of connection weights to bring four pairs of subsymbols into

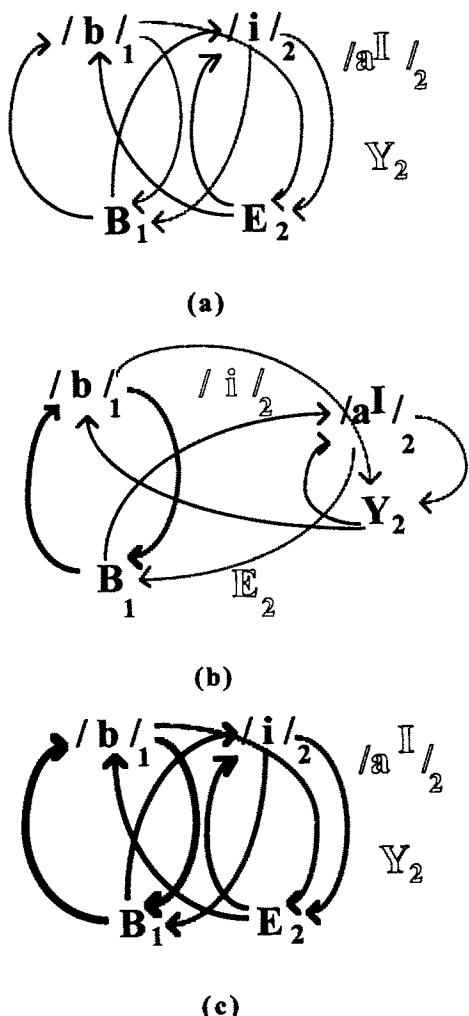


Figure 3. A simplified illustration of self-consistent cross talk in a recurrent network. a: The consequences for the connections between the visual subsymbols (bottommost in each panel) and phonologic subsymbols (topmost in each panel) of a learning trial for the word BE. b: Likewise for the word BY. c: A second learning trial for the word BE. A line between two subsymbols indicates an increase in connection weights between those two subsymbols. The width of the lines ranks the self-consistency of the relations that accumulates across learning trials. Notice across panels that the self-consistency (width of the lines) between B_1 and $/b_1$ increases faster than the self-consistency of other relations.

collective resonance: $B_1 \leftrightarrow /b_1$, $B_1 \leftrightarrow /i_2$, $E_2 \leftrightarrow /b_1$, and $E_2 \leftrightarrow /i_2$. Subsequently, a BY trial, shown in Figure 3b, adjusts four pairs of connection weights to bring its four pairs of subsymbols into collective resonance: $B_1 \leftrightarrow /b_1$, $B_1 \leftrightarrow /a^I_2$, $Y_2 \leftrightarrow /b_1$, and $Y_2 \leftrightarrow /a^I_2$. If, in turn, another BE learning trial occurs (3c), then the four pairs of connection weights ($B_1 \leftrightarrow /b_1$, $B_1 \leftrightarrow /i_2$, $E_2 \leftrightarrow /b_1$, and $E_2 \leftrightarrow /i_2$) are adjusted again to promote its four component resonances. It is important to note that the only changes across these trials are fine-grain changes between pairs of subsymbols, but these changes track form–function correlations at any grain size equal to, or coarser than, the grain size of the subsymbols. At the finest grain size, because B correlates with the same phonology in BY and BE, the configuration of weights promoting the resonance $B_1 \leftrightarrow /b_1$ is tuned toward a single strong attractor more often than configurations promoting other component resonances. It emerges as a “strong rule,” a strong fine-grain attractor. Once learned, the component fine-grain resonances of a strong-rule word or pseudoword coalesce relatively quickly and facilitate naming. Consequently, even an unfamiliar word composed of strong rules may be named quickly (Rosson, 1985). Strong-rule resonances, such as $B \leftrightarrow /b_1$, are examples of local (fine-grain) dynamics exhibiting high self-consistency. (Notice that covariant learning and self-consistency are confounded in this illustration.)

The self-consistency principle is observed in models that implement harmony theory (Smolensky, 1986a, 1986b), Boltzman machines (Hinton & Sejnowski, 1986), and adaptive resonant filter theory (Grossberg, 1982), and it is the crux of the interactive activation model (Grainger & Jacobs, 1994a; McClelland & Rumelhart, 1981). Self-consistency effects are due to the strength of the feedback received by a set of subsymbols, relative to competitors that also receive feedback. Put another way, self-consistency estimates subsymbols' capacity to conserve their own activation. Subsymbols conserve their activation when they “send” it to other subsymbols that will “return” that activation in relatively exclusive feedback. Conservation depends on the strength of associations developed between subsymbols. For the letter B, the visual phonologic resonance $B \leftrightarrow /b_1$ is a strong attractor; few other sound patterns in English correspond with B, and few other spelling patterns correspond with $/b_1$. This bidirectional consistent cross talk is the basis of strong self-consistency. Inconsistent cross talk, in either direction, dissipates activation and increases the competition for resonance. For example, activation from B to semantic subsymbols results in diffuse, incoherent feedback because a huge variety of semantic subsymbols correspond with words that contain B.

Frequency of previous occurrence also affects the likelihood of resonance. As noted, strongly self-consistent relations correspond to strong attractors, so fine-grain self-consistent relations, such as $B_1 \leftrightarrow /b_1$, yield powerful fine-grain attractors that cohere faster than less self-consistent relations (cf. Berent & Perfetti, in press). Likewise, the relatively strong, fine-grain, form–function relations that make up high-frequency words (e.g., $B_1 \leftrightarrow /b_1$, $B_1 \leftrightarrow /i_2$, $E_2 \leftrightarrow /b_1$, and $E_2 \leftrightarrow /i_2$ in Figure 3) combine their effects in

strong, coarse-grain, word-size attractors ($B_1E_2 \leftrightarrow b_1i_2$) that cohere well before those of low-frequency words. We demonstrate next that performance in simple reading tasks is predicted by such nested correlations between visual forms and linguistic functions.

Fine-Grain Self-Consistency

As already noted, strong-rule words and pseudowords are named faster and more accurately than weak-rule words and pseudowords. Rule-strength effects emerge from fine-grain, visual–phonologic self-consistency. Letters and phonemes occur together much more frequently than the syllables and words they compose. Moreover, the covariation between many letters and phonemes is relatively consistent (“regular”), which insures consistent cross talk. These fine-grain pockets of self-consistency are typically the strongest local attractors, so they cohere quickly and supply early local constraints in word perception. “Regular,” fine-grain, visual–phonologic attractors have been interpreted as grapheme–phoneme correspondence (GPC) rules (M. Coltheart, 1978; M. Coltheart et al., 1993). Symbolic analyses seek invariant regularities that qualify as rules. In contrast, we assume a more inclusive, statistical form of regularity (Jared, McRae, & Seidenberg, 1990; Van Orden et al., 1990). The special case of invariance is merely a form–function correlation that approaches unity.

Intermediate-Grain Self-Consistency

Prinzmetal and his colleagues have observed provocative effects of intermediate-grain self-consistency (Prinzmetal, 1981, 1990; Prinzmetal, Hoffman, & Vest, 1991; Prinzmetal & Keysar, 1989; Prinzmetal & Millis-Wright, 1984; Prinzmetal, Treiman, & Rho, 1986; see also Rapp, 1992; Seidenberg, 1987). Prinzmetal’s results demonstrate that “low-level” visual perception is shaped by “high-level” cognitive dynamics. Specifically, illusory conjunctions (Treisman & Schmidt, 1982) and neon-color illusions (Van Tuijl, 1975) track the self-consistency of printed words’ visual–linguistic correspondence.

In Prinzmetal’s illusory conjunction paradigm, a target letter, such as D, is presented in white. This target is followed by a briefly presented, colored letter string such as VODKA. The subject’s task is to identify the color of the target letter D, as it appears in VODKA. On an example trial, V and O might be red, while D, K, and A are green. An illusory conjunction occurs if the subject calls the green D red. In words such as VODKA, the phonologic syllable boundaries are correlated with typical boundary patterns of spelling (i.e., “syllable boundaries were formed by two consonants that do not occur together within a syllable in English spelling”—Prinzmetal et al., 1991, p. 903). Thus, the interior boundaries of the stimulus words’ syllables are relatively self-consistent; features to either side of the phonologic boundary covary consistently with the respective features on either side of the spelling boundary. Surprisingly, illusory conjunctions tend to preserve these

self-consistent boundaries (i.e., D is erroneously called “red” to match the other letters on its side of the boundary; Prinzmetal et al., 1986, 1991; Seidenberg, 1987).

In a neon-color experiment, letters were overlaid with neon-color grids (Prinzmetal, 1990). For the example VODKA, VO appeared with a red grid overlay, D was overlaid with an ambiguous plaid of red and green, and KA was overlaid with a green grid. Subjects identified the color of the objectively ambiguous D by selecting a best matching color chip. Subjects were most likely to choose a color for D to match the hue of D’s syllable (VOD__ in the example). This effect was equally strong for pseudowords, such as VOBKA.

Other experiments examined syllable boundaries that were low in self-consistency. For example, the word NAIVE contains a letter pair AI that occurs relatively inconsistently with NAIVE’s syllable boundary (consider WAIVE, PAIN, NAIL, NAIROBI, SAID, etc.). Most words containing AI suggest these letters should correspond to a single phoneme. Consequently, in visual–phonologic dynamics, most competing relations provide feedback grouping AI together. In a neon-color experiment (Prinzmetal, 1990), subjects’ performance matched the majority opinion; they were most likely to identify I’s color to match A. Seidenberg (1987) observed a parallel effect using the illusory conjunction paradigm. However, in a different illusory conjunction experiment, Prinzmetal et al. (1991, Experiment 1) observed a nonsignificant trend in the direction that respects NAIVE’s phonologic syllables. Overall, then, no dominant pattern has emerged from studies using syllable boundaries with low self-consistency. However, syllables with highly self-consistent boundaries reliably shape color perception.

Other statistical effects are also correlated with intermediate-grain self-consistency. Neighborhood effects that are observed in various tasks may reflect intermediate-grain self-consistency (Andrews, 1989, 1992; M. Coltheart, Davelaar, Jonasson, & Besner, 1977; Glushko, 1979; Jared et al., 1990; Taraban & McClelland, 1987). We suggest that careful attention to self-consistency may help resolve the contentious debate concerning the precise character of neighborhood effects, or even their reliability (see Massaro & Cohen, 1994). For example, neighborhood frequency estimates are better predictors of word recognition speed than neighborhood size estimates (Grainger & Jacobs, 1993; Grainger, O’Regan, Jacobs, & Segui, 1989, 1992; Jacobs & Grainger, 1992). Neighborhood frequency is also a slightly better estimate of a word’s attractor topology, in terms of strength of cross talk. Thus far, however, most neighborhood experiments have ignored phonology, so consistency of cross talk has been ignored. Experiments such as those of Jared et al. (1990), demonstrate the value of this consideration.

Coarse-Grain Self-Consistency

The perceptual and empirical unity (holism) of a word’s form with its linguistic function is due to word size (coarse-

grain) self-consistency (cf. Drewnowski, 1981; Healy, 1976). Of course, like intermediate-grain self-consistency, coarse-grain self-consistency is tracked in fine-grain connection strengths; thus, its effects are emergent in dynamics. This frees us from explicit, whole-word mechanisms such as direct access. There is no better example of emergent coarse-grain effects than phonologic mediation.

Phonologic Mediation

In English, visual–phonologic resonances cohere before visual–semantic resonances in word perception. In alphabetic languages like English, the primacy of visual–phonologic dynamics is guaranteed. Fine- and intermediate-grain self-consistency between visual forms and phonologic functions is generally much greater than the coarse-grain self-consistency between these surface patterns and meaning. Moreover, although frequency greatly strengthens a word's visual–phonologic dynamics, word frequency and consistency of meaning are not so correlated. The more frequent a word, the greater the variety of meanings it will typically express (Jastrzembski, 1981). In covariant learning, a word's coarse-grain visual–phonologic attractor must become stronger than the complementary attractors forming between the visual pattern and meanings. Consequently, even nonalphabetic coarse-grain characters will exhibit powerful phonologic constraints in word perception (Wydell, Patterson, & Humphreys, 1993). The resonance that emerges between visual and phonologic features is thus a coherent foundation for building “higher level” resonances. This is the phonologic coherence hypothesis (Van Orden, 1991; Van Orden et al., 1990).

Phonology mediates word perception through early local coherence. Notice that the sense of *mediate* implied by the phonologic coherence hypothesis is not the sense of *mediate* that derives from flowchart models (e.g., M. Coltheart, 1978). *Mediate* has several definitions as a transitive and intransitive verb; these are listed in the *American Heritage Dictionary* (Morris, 1982):

—*tr.* 1. To resolve or settle (differences) by acting as an intermediary agent between two or more conflicting parties. 2. To bring about (a settlement, for example) by action as an intermediary. 3. *To convey or transmit as an intermediary agent or mechanism* [italics added]. —*intr.* 1. To intervene between two or more disputing parties in order to effect an agreement, settlement or compromise. 2. To settle or reconcile differences.

Linear flowchart models make exclusive use of meaning number 3 for the transitive form of the verb (the italicized meaning) (e.g., Van Orden, Johnston, & Hale, 1988). This is why phonologic mediation appears inefficient and counterintuitive (Paap, Noel, & Johansen, 1992; Seidenberg, 1992). Why should information processing traverse the same psychological distance in two steps (Step 1: orthography to phonology; Step 2: phonology to lexicon) rather than one step (orthography to lexicon)? To retain economy of processing, prominent theories of skilled reading remain “stubbornly nonphonological” (Liberman, 1991, p. 242), clinging

tenaciously to null phonology effects (V. Coltheart, Avons, Masterson, & Laxon, 1991; Fleming, 1993; Jared & Seidenberg, 1991; Seidenberg, 1992), despite the wealth of positive demonstrations of phonology's mediating effect on perception of printed words (Carey, Turvey, & Lukatela, 1992; Lukatela & Turvey, 1994; Perfetti, Zhang, & Berent, 1992; Van Orden et al., 1990). Van Orden et al. (1992, pp. 281–282) criticized this habit of accepting the null hypothesis:

Failures of phonologic hypotheses predicated on a symbolic human-information-processing metaphor eroded phonology's role in theories of printed word [perception]. These failures were also taken as converging evidence supporting “nonphonologic” hypotheses, “the sole alternative” to phonologic hypotheses. Of course, psychology's conventions of hypothesis testing disallow accepting the null hypothesis. In practice, however, highly visible null findings often “confirm” positive hypotheses.... The absence of positive support for “sole alternative” nonphonologic hypotheses, coupled with repeated failures of phonologic hypotheses, should have alerted theorists to inherent fallacies in the symbolic analysis. Instead, theorists accepted the null hypothesis and reduced or eliminated phonology's role in reading.

Inferences that derive from null effects originate in axiomatic assumptions made for intuitive tractability and to explain positive experimental effects (Posner, 1978; Sternberg, 1969). These are the familiar assumptions that cognitive systems are truly linear systems and are fully transparent with respect to data. Too much faith in these axioms, however, leads to tautology: The presence or absence of an effect indicates the presence or absence of a mental process.

The phonologic coherence hypothesis provides an economical interpretation of phonology's mediating effect on word perception. Coincidentally, its dynamic metaphor invokes all the remaining definitions of *mediate* listed previously—the meanings overlooked by flowchart models. Self-consistent feedback from phonology rapidly organizes the system, “mediating” local competitions that would organize the visual stimulus. Subsequently, a coherent visual–phonologic dynamic “mediates” competitions among alternative global interpretations—their chances for survival are enhanced if they conform to extant, visual–phonologic dynamics. In this system, phonologic “mediation” is inescapable, due to the powerfully self-consistent, visual–phonologic attractor topology. In high-frequency words, visual–phonologic resonance can be achieved so quickly that perception appears direct. Thus, inferring a direct nonphonologic route for high-frequency words overinterprets a ceiling effect (see also Lukatela & Turvey, 1994).

Phonologic mediation is demonstrated empirically when effects due to semantic properties of a word (e.g., ROSE) are mediated by presentation of its homophone (ROWS) or pseudohomophone (ROZE). The most direct evidence of phonologic mediation comes from experiments in which homophones or pseudohomophones are misidentified as their homophonic mate. For example, subjects in a semantic categorization task typically make many false-positive errors to homophone foils (e.g., ROWS or ROZE misidentified as A FLOWER), in comparison to control foils, even

when subjects get a good look at the homophone foils (Banks, Oka, & Shugarman, 1981; V. Coltheart et al., 1991; Jared & Seidenberg, 1991; Llewellen et al., 1993; Meyer & Gutschera, 1975; Nielson, 1991; Nielson & Van Orden, 1992; Peter & Turvey, in press; Van Orden, 1987; Van Orden et al., 1988, 1992). Wydell et al. (1993) recently reported a dramatic demonstration of this effect. They observed inflated categorization error rates to Japanese Kanji homophones. Kanji characters lack the alphabetic properties thought to promote phonologic mediation, so Wydell et al.'s study provides an unexpected demonstration of phonologic mediation. However, even in Kanji, the visual forms of words are more strongly correlated with their names than their meanings. Thus, visual-phonologic resonances should precede visual-semantic resonances. (Of course, some languages do not respect this pattern. Chinese characters can be at least as strongly correlated with semantic features as with phonology, which predicts early semantic coherence; see Perfetti et al., 1992.)

To summarize, phonologic mediation is explained by the phonologic coherence hypothesis, which derives from two design principles: covariant learning and self-consistency. Highly self-consistent relations correspond to resonances that are strongly self-perpetuating. They are more likely to survive competitive dynamics than less self-consistent relations, and they constrain global dynamics toward a state consonant with their survival. Covariant learning tracks the self-consistency of form-function relations, including the relations among words' visual forms, their phonology, and the complex variety of their meanings. Dynamics are drawn toward successive local attractors reflecting "expected values" from previous experience, and eventually, to the word-size global attractor that strikes the best balance among local attractors (i.e., the global attractor that best mediates lasting dispositions and contextual eccentricities). This description, which is based on two simple design principles, provides a coherent account of many effects beyond categorization errors (see Lukatela, Lukatela, Carello, & Turvey, 1994; Van Orden & Goldinger, 1994; Van Orden et al., 1990). Next, we apply it to recent findings from naming and lexical decision experiments.

Naming

Figure 4 depicts a performance topology derived from representative naming and lexical decision experiments. Read Figure 4 from the middle upward for naming data and from the middle downward for lexical decision data. Beginning in the middle, correct word naming times are depicted to the left of correct "word" lexical decision times, because naming times are generally faster than "word" lexical decision times (when lexical decision experiments include pronounceable nonword foils; Forster & Chambers, 1973; Llewellen et al., 1993; Waters & Seidenberg, 1985).

Balloon N₁. Moving up from the middle, data balloon N₁ zooms in on naming times from Waters and Seidenberg (1985). It rank orders naming times, from fastest to slowest, beginning with very high-frequency words of all types (the

leftmost point). Of course, faster naming of high-frequency words is a consequence of the strong nested correlations inherent in their high-frequency relations. As we noted previously, the form-function relations in high-frequency words yield strongly self-consistent, word size attractors that quickly cohere. Fast resonance supports fast naming. Indeed, even simple nonrecurrent networks code high-frequency relations virtually "noise-free" (Seidenberg & McClelland, 1989; Van Orden, 1987), ensuring fast naming times.

Moving to the right in data balloon N₁, the next three points correspond, in turn, to low-frequency regular words, such as MINT, whose phonology is typical of English spelling-sound correspondence; followed by low-frequency irregular words, such as PINT, whose phonology is atypical when compared to words with similar spellings; and strange words, such as CHOIR, which have strange phonology with respect to typical English spelling-sound correspondences. The visual-phonologic relations in these words lie along a continuum of self-consistency, in line with their naming times (Van Orden et al., 1990). The self-consistency of the regular word MINT is relatively high, because its fine-grain (e.g., M-/m/, I-/I/) and intermediate-grain (e.g., INT-/Int/) relations are shared by many words (e.g., LINT, HINT, MIST, MITT, SIN, etc.). The irregular word PINT goes against these strong correlations in its vowel phonology, so its overall visual-phonologic self-consistency is lower than that of MINT. However, it is more self-consistent than the strange word CHOIR, which is composed of several poorly correlated relations (a more consistent pronunciation of CHOIR would include CH as in CHEESY, OI as in BOISE, etc.).

Balloon N₁₁. Balloon N₁₁ depicts a more fine-grained analysis of naming times from Jared et al. (1990). It zooms in on low-frequency regular and irregular words. The categories are based on whether a word's phonology is consistent with its neighbors' (MATE and HATE are consistent neighbors; MINT and PINT are inconsistent neighbors). When words are inconsistent, they are ranked by the relative summed frequency of their "friends" and "enemies" (TINT is a friend to MINT; PINT is MINT's enemy). The relative summed frequency of friends and enemies is a fair estimate of the cross talk in these neighborhoods, indicating the relative self-consistency of the competing subword relations. For low-frequency words, the time course and outcome of competition are predicted by the self-consistencies of competing local relations. A word with high summed-frequency friends has strong local attractors promoting fast, correct performance. Friendly local attractors pull dynamics toward correct phonology; enemy attractors pull dynamics toward incorrect phonology (e.g., PINT is pulled toward rhyming with MINT). When the enemy attractors have low summed frequency, friend attractors make short work of enemies and a fast, correct naming response is observed.

When friends and enemies have approximately equal frequencies, the outcome of dynamics depends more on the strength of the target word's global (word size) attractor. The global resonances of low-frequency relations emerge more slowly than resonances of high-frequency relations.

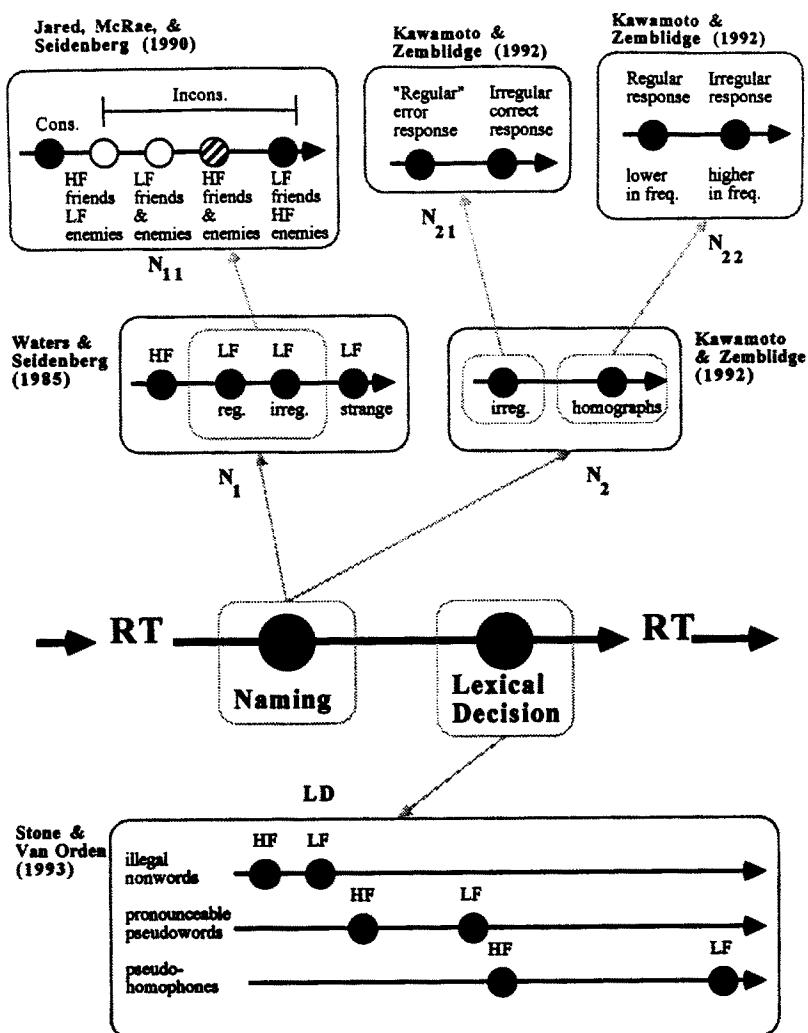


Figure 4. A performance topology derived from prior experiments on printed word naming (N) and lexical decision (LD). The illustrated naming experiments examined performance to words that vary in self-consistency. The illustrated lexical decision experiment manipulated the types of nonwords (e.g., BTNI, BINT, and HEET), but tested for an effect in performance to high- and low-frequency words. Cons. = consistent; Incons. = inconsistent; HF = high frequency; LF = low frequency; freq. = frequency; RT = reaction time; reg. = regular; irreg. = irregular.

They depend on contextual constraints (such as the contextual constraints M_1/I_1 , N_3/I_2 , T_4/I_2 that pull MINT toward correct phonology) and feedback from semantic subsymbols. These constraints eventually inhibit enemy attractors, but they are most effective against weak enemies. As should now be obvious, the worst case in balloon N_{11} corresponds to weak, correct, local attractors (low-frequency friends, or no friends) that face powerful enemy attractors (high-frequency enemies). In this case, feedback from semantics is crucial for correct performance, so we expect the slowest correct naming times and the most errors (Kawamoto & Zembilidge, 1992).

The rank order shown in data balloon N_{11} agrees with our analysis, in terms of nested form–function relations. Moving from left to right, consistent words are named a bit faster

than inconsistent words with low-frequency enemies and high-frequency friends, but these naming times are statistically indistinguishable (Jared et al., 1990). Likewise, naming times to inconsistent words with low-frequency friends and enemies appear slower still, but they are not statistically different from naming times to consistent words. Naming times to inconsistent words with high-frequency friends and enemies are significantly slower than naming times to consistent words when data are grouped by subjects but not by items. Finally, naming times to inconsistent words with high-frequency enemies and low-frequency friends are reliably slower than naming times to consistent words in both analyses. The rank order of naming times is an apparent match to the rank-ordered estimate of self-consistency among competing form–function relations.

Balloon N₂. Balloon N₂ depicts naming times to irregular words, such as PINT, and to homographs, such as LEAD, that have both typical (to rhyme with DEED) and atypical (to rhyme with DEAD) phonology (Kawamoto & Zemblidge, 1992). We came across irregular words before in data balloons N₁ and N₁₁; we know that their local, irregular, form–function relations compete with strong regular relations, and this competition slows naming times. However, naming times to homographs are slower still. Irregular words have singular, correct, visual–phonologic attractors, but homographs do not. Homographs support more than one coarse-grain attractor state, so fierce competition occurs at all grain sizes of visual–phonologic correspondence. This more contentious dynamic is reflected in exaggerated naming times.

Balloon N₂₁. Balloon N₂₁ zooms in on correct and incorrect naming times to irregular words, such as PINT. In an experiment conducted by Kawamoto and Zemblidge (1992), PINT was misnamed to rhyme with MINT on about 25% of trials. More interesting, the naming times for these “regularization errors” to PINT were faster than *correct* irregular responses (601 ms vs. 711 ms). From the discussion of data balloon N₁₁, we know this phenomenon would be most likely when irregular words have substructure common to many regular enemy words and have weak friends. In this case, the most self-consistent local relations would be regular relations. For a correct naming response, this false-positive dynamic structure must be inhibited. Correct naming requires that some other source of constraint (e.g., PINT’s correct phonologic–semantic attractor) counter the false-positive local attractors. Because correct naming times are slower than incorrect naming times, correct performance must rely on constraints that emerge after enemy visual–phonologic attractors begin to cohere. Consequently, phonologic–semantic dynamics must cohere later than visual–phonologic dynamics.

Balloon N₂₂. Balloon N₂₂ illustrates a similar phenomenon—naming times for the regular pronunciations of homographs (e.g., LEAD named to rhyme with DEED) are typically faster than naming times for irregular pronunciations (e.g., LEAD named to rhyme with DEAD). This is true even if the irregular pronunciations are more familiar to subjects (Kawamoto & Zemblidge, 1992). Again, the early coherence of local regular attractors supports faster naming, and performance specified by more global constraints emerges more slowly. Kawamoto and Zemblidge simulated this performance profile in an attractor network. In their simulation, dynamics traveled initially toward local, regular, visual–phonologic attractors but were usually captured by the word size attractor that maximized global self-consistency.

Pulling back from the details of Figure 4, we note the complex variety of effects that are explained by two design principles: covariant learning and self-consistency. To predict these complex patterns, we have merely tracked the nested structure of words’ form–function relations. Nonetheless, our simple description predicts coarse-grain phenomena like phonologic mediation, intermediate-grain phenomena such as the syllable boundaries that are respected in

illusory conjunctions, and fine-grain, statistical regularity effects on printed word naming. These effects are self-similar, as they all reflect ambiguity at various grain sizes. Self-similarity at all scales of observation is a marker of systems organized by recurrent feedback (Peitgen et al., 1992). Recent applications of chaos theory suggest that self-similar geometric phenomena may be ubiquitous in nature. Natural self-similar phenomena—analogous to mathematical idealizations such as the Mandelbrot set—exhibit similar structure when looked at from far or near vantage points. As examples, Gleick (1987) noted the branching structures of blood vessels at all levels of description (from major arteries to capillaries), the local and global disturbances created in earthquakes, and the branching proteins in goose down.

In this section, we illustrated the self-similar structure in printed word naming: Basic design principles describe the behavior equally at local and global levels of observation. The advantage of this approach is the elegant simplicity we discover in these complex data patterns. Consider also the nonword naming data reported in this volume by Seidenberg et al. (1994): The self-consistency of nonword pronunciations predicts their naming times. Nonword naming apparently is described by the same design principles, yielding another view of this self-similar structure. Of course, the data summarized in Figure 4 are explained by many models in the word recognition literature (including models in this issue). Extant models use a variety of mechanisms to fit the behavioral data. For example, the most recent dual-route models use rules of varying sizes and strengths (M. Coltheart et al., 1993; Paap et al., 1992), and connectionist models use distributed networks with connections of varying strengths (e.g., Kawamoto, 1988, 1993, in press; Seidenberg & McClelland, 1989; Seidenberg et al., 1994; Van Orden, 1987). Other models in the literature use analogous mechanisms to mimic the same profile of performance. We have so many models because the contemporary Zeitgeist pressures researchers to provide models and engage in strong inference.

Because our theoretical framework is built on design principles, it is, by definition, abstracted from the reliable data and the successful models in the literature. Consider the battles currently waged between the dual-route and connectionist approaches (see Seidenberg et al., 1994). Although the models differ in their specific architectures, the behaviors of both models converge along most studied dimensions. For example, aspects of covariant learning are approximated by rule derivation and strengthening in the dual-route model and by changes in connection strengths in the connectionist model. These models are not in competition with our framework because there is no basis for competition—models cannot be contrasted with the design principles that they implement. We have avoided discussion of models’ idiosyncratic behavior. We certainly value strong inference and the importance of testing models,⁴ but the eventual goal is to discover reliable design principles.

⁴ Indeed, the history of the dual-route theory shows the value of strong inference, as a necessary process to discover design prin-

As we have seen, a focus on design principles, combined with a perspective from chaos theory, organizes decades of data into a simple self-similar geometry. Next, we apply these design principles to lexical decision performance.

Lexical Decision

A naming response is specified when visual and phonologic subsymbols cohere in resonance. A lexical decision response, on the other hand, is specified when the system states consequent on word stimuli can be distinguished from system states consequent on nonword stimuli. We propose that words are rendered distinguishable from nonwords by the degree of coherent (vs. incoherent) activity among visual, phonologic, and semantic subsymbols (see also Lewenstein & Nowak, 1989). To understand this proposal, recall the initial conditions that follow presentation of a word or nonword. Stimulus presentation initiates a diffuse incoherent pattern of activation, including all associated phonologic and semantic subsymbols. Degree of activation is isomorphic with previous association strength.

In the initial state, as we noted earlier, the only apparent structure in the system derives from the narrative identities of the subsymbols. Behaviorally meaningful structure only emerges in feedback dynamics. For example, meaningful orthographic structure is a consequence of visual–linguistic dynamics; it does not originate in discrete, *a priori* spelling representations, as is widely assumed. The implication for lexical decision is that initial conditions cannot distinguish words and nonwords. Both produce initial states of diffuse incoherent activation.

Consider next how activation patterns change following initial conditions. Cooperative–competitive dynamics conserve activation of subsymbols that participate in strongly self-consistent relations and inhibit subsymbols of competing, weaker relations. For words, this organizes the system into an increasingly coherent set of active subsymbols, maintained by learned global attractors. Movement toward globally coherent states is equivalent to increasing the information in the system, in the formal sense of information as reduction of uncertainty. The system settles on one global attractor state from a vast set of potential attractors that are latent in the initial conditions. Notice that information emerges locally from the form–function relations inherent in a perceptual event (see Turvey & Carello, 1981).

One estimate of global coherence (information) in an implemented model is the extent to which feedback from linguistic subsymbols matches the activation of visual subsymbols. Computationally, this is a mismatch vector in

ciples. Coltheart's (1978) seminal description of the dual-route model has been challenged by contradictory data, and it has been modified—bit by bit. Now, as Seidenberg et al. (1994) discuss, the dual-route model can account for most of the relevant data, but it has become virtually isomorphic to a connectionist model. The strong inference process, combined with freedom to modify models, eventually forces competing models to a point of behavioral identity—a point within the shaded region of Figure 1, the region illustrating induction of design principles.

which each element measures a difference between the “expectations” of phonologic and semantic subsymbols that are fed back to a particular visual subsymbol, and the actual state of that visual subsymbol (cf. Grossberg & Stone, 1986; Plaut & Shallice, in press; Seidenberg & McClelland, 1989; Stone & Van Orden, 1989, 1993). The coherence of a local dynamic increases as its vector element approaches zero (zero equals no difference—a perfect match between expected and actual activation of visual subsymbols). The overall, global coherence of dynamics is indicated by the overall length of this mismatch vector. Thus, as the global coherence in the system increases, the system has more information to specify a response (see Figure 5). Ideally, as dynamics approach resonance, the elements of a word's mismatch vector approach zero. In contrast, the elements of a nonword's mismatch vector should remain nonzero, because a nonword never fully matches learned expectations. Thus, ideally, all words may be deterministically sifted from nonwords.

Of course, actual dynamics are less than ideal. In a more realistic account, the global coherence of words and nonwords will constitute partially overlapping distributions (Balota & Chumbley, 1984). The amount of overlap will change over time, as dynamics converge on the maximally coherent state that a stimulus will sustain. In the course of dynamics, words will eventually grow more coherent than nonwords. How coherent they must be for reliable lexical decisions depends on the similarity of the nonwords to actual words (see Figure 5), presuming that subjects adjust their “criteria” accordingly.

Return now to the middle of Figure 4. Lexical decision times are depicted as generally slower than naming times when the nonword foils are pronounceable pseudowords, such as BINT (Forster & Chambers, 1973; Llewellen et al., 1993; Waters & Seidenberg, 1985). This is because BINT cannot be distinguished from PINT (for example) until surface–semantic dynamics begin to cohere. Pseudowords, such as BINT, are spelled in a fashion that supports visual–phonologic dynamics common to many words. Early on, increasingly coherent visual–phonologic dynamics will reduce the mismatch vectors of both BINT and PINT (consonant with the phonologic coherence hypothesis). Only later, in surface–semantic dynamics, will the difference in global coherence exceed some critical value. Typical lexical decision responses, specified in surface–meaning relations, will be slower than naming responses, specified in visual–phonologic relations.

In Figure 4, balloon LD zooms in on lexical decision times from an experiment by Stone and Van Orden (1993) that manipulated printed word frequency (high vs. low) and the type of nonword foils. In all conditions, response times to high-frequency words were faster than to low-frequency words, replicating the most prominent effect in lexical decision performance. However, overall performance and the relative size of the frequency effect changed across the three nonword conditions.

The condition shown in the middle of data balloon LD is the pronounceable pseudoword (BINT) condition. This condition is the typical version of lexical decision; it produces

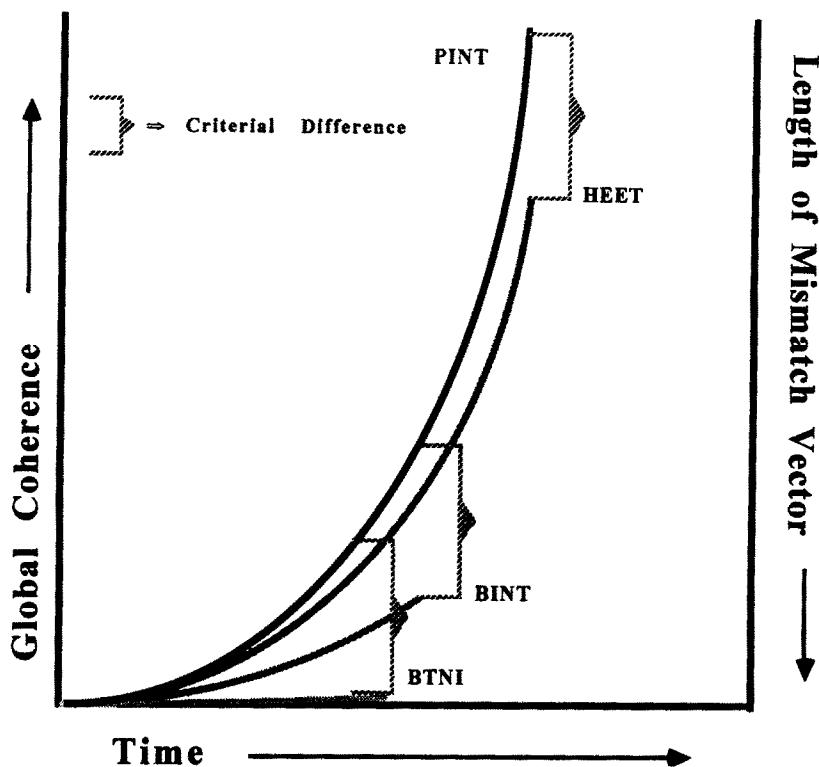


Figure 5. Global coherence of dynamics, over time, following presentation of a real word (PINT), a pseudohomophone (HEET), a legal nonword (BINT), and an illegal nonword (BTNI). When differences in global coherence (or correspondingly, differences in the length of mismatch vectors) between words and nonwords reach criterion, discrimination is possible.

a frequency effect intermediate between the other two nonword conditions. The frequency effect occurs because dynamics accelerate toward resonance more quickly for high-frequency words than for low-frequency words, and the dynamics of high-frequency words deviate less from straight trajectories. Overall, the form–function relations of high-frequency words are more self-consistent than those of low-frequency words, so they move to their global attractor states with less resistance from competing attractors. Consequently, high-frequency words may be distinguished from nonwords earlier in dynamics. Because this is a difference in the acceleration of dynamics, the advantage for high-frequency words grows over time (Stone & Van Orden, 1993).

An analogous acceleration advantage is seen in a drag race, when the dragster (or monster truck) with greater acceleration pulls away steadily from the trailing vehicle. As the distance between the two dragsters grows, so grows the difference in their finishing times. If we measure at three successive points, the difference between finishing times will grow, along with the overall finishing times. These three successive finishing points are analogous to the three successive system states in Figure 5 at which words may be discriminated from illegal nonwords (BTNI), pronounceable pseudowords (BINT), and pseudohomophones (HEET).

The fastest overall performance occurs when words must be distinguished from illegal nonwords, such as BTNI (the top line in balloon LD). Illegal nonwords are constructed from odd combinations of letters that, together, are relatively unpronounceable. Likewise, in a model, illegal nonwords cannot support coherent visual–phonologic dynamics. Once real words’ visual–phonologic dynamics begin to cohere, they quickly become discriminable from illegal nonwords. This system state occurs very early in the dynamics of word perception, at similar rates for high- and low-frequency words—akin to a very short drag race. As a result, the difference in response times between high- and low-frequency words is smallest in this condition. It is also interesting to note that the mean lexical decision time and the magnitude of the frequency effect, which rely only on early visual–phonologic coherence, are within the range of those observed in naming experiments, where performance also depends only on fully coherent visual–phonologic dynamics.

Move now to the bottom line in balloon LD. Overall response times are slowest, and the frequency effect is very large, when words must be distinguished from pseudohomophones such as HEET. Pseudohomophones mimic the phonology of actual words, and the visual–phonologic dynamics of pseudohomophones include relations common to many words. No fine- or intermediate-

grain relations unambiguously favor HEAT over HEET for the phonology of /hēt/ (many words use EA-/ē/ and EE-/ē/). Additionally, because the phonologic–semantic dynamics driven by the stimuli HEAT and HEET are identical, HEET \leftrightarrow /hēt/ receives false-positive feedback from semantic subsymbols. The only bases for distinguishing words from pseudohomophones are small differences in spelling. Therefore, correct lexical decisions rely crucially on the dynamic between visual and semantic subsymbols.

We have already claimed for English that visual–semantic relations never cohere before visual–phonologic relations, and they are typically the last relations to cohere in word perception (Van Orden & Goldinger, 1994; Van Orden et al., 1990). As noted, the self-consistency of visual–phonologic relations is much greater than that for visual–semantic relations. Additionally, the self-consistency of phonologic–semantic relations is greater than that of corresponding visual–semantic relations, because speech is much more common than reading. Thus, there is no possibility of visual–semantic dynamics cohering until all other dynamics are relatively stable.

We also believe that this asymmetry is self-perpetuating, once in place. Reading strengthens phonologic–semantic self-consistency, because phonology functions in every instance of printed word perception. Additionally, conversation strengthens phonologic–semantic self-consistency, because spoken language is specified in phonologic–semantic states. Thus, the greater relative self-consistency of phonologic–semantic relations is assured. In principle, if phonologic–semantic dynamics cohere before visual–semantic dynamics, then printed and spoken discourse can proceed without resolving visual–semantic dynamics. Perhaps this explains the asymmetry often found between reading and spelling (most adults read better than they spell—e.g., see Bosman, 1994). Spelling, especially spelling of irregular words, relies on weaker, less self-consistent, visual–semantic relations. In the present case, this asymmetry implies that lexical decision requires complete resolution of visual–phonologic–semantic dynamics before words can be distinguished from pseudohomophones, such as HEET. It makes sense then that the pseudohomophone condition produces very slow overall response times and a very large frequency effect. Dynamics must run their full course to global coherence before system states reliably discriminate words from pseudohomophones.

Perception of PINT

Figure 6 illustrates perception of PINT; this figure summarizes our analysis. (Figure 6 simplifies the state space, including only those states on PINT’s trajectory that illustrate selected points of argument.) Perception of PINT begins at the left side of the figure, the point at which PINT is presented and initial conditions arise. Initial conditions, portrayed in the faint rectangle, include diffuse, incoherent activation across many phonologic and semantic subsymbols (e.g., *container*, /m/, /a/, *balance*, /b/, /l/, /t/, etc.),

including many subsymbols that will be inhibited in subsequent dynamics (e.g., /m/, /o/, *excess*, etc.). (The semantic subsymbols illustrated as *such* denote image schemas.) Of course, PINT is explicit in the left-most point of the figure (the experimenter’s view), but it only becomes explicit in perception (the subject’s view) as a consequence of dynamics beyond the initial conditions.

Moving to the right, the first structured dynamics reflect fine- and intermediate-grain visual–phonologic relations, because they are the most self-consistent form–function relations in word perception. These early dynamic structures are indicated by PINT’s looping connections to /pInt/ and /pa^lnt/. As described earlier, the dynamic PINT \leftrightarrow /pInt/ is initially more self-consistent than PINT \leftrightarrow /pa^lnt/. This is shown in Figure 6 by placing /pInt/ to the left of /pa^lnt/, indicating earlier coherence for /pInt/. At this point, although the correct dynamic is weaker, the increased coherence of the system from initial conditions would still distinguish PINT from illegal nonwords, as indicated by the broken vertical line that descends from BTNI.

Continuing to the right, the correct visual–phonologic resonance of an irregular word like PINT relies on phonologic–semantic dynamics to overcome the false-positive attractor PINT \leftrightarrow /pInt/ (Kawamoto & Zemblidge, 1992). In Figure 6, this is shown by faint loops indicating the dynamics emerging between /pa^lnt/ and semantic subsymbols. Visual–phonologic dynamics eventually coalesce into an attractor state (PINT \leftrightarrow /pa^lnt/) that best agrees with emerging phonologic–semantic dynamics. This resonance is symbolized by the bold loop between PINT and /pa^lnt/. After this first attractor state is established, phonologic–semantic dynamics continue toward resonance. In Figure 6, these continuing dynamics are shown as bolder loops between /pa^lnt/ and semantic subsymbols after PINT \leftrightarrow /pa^lnt/ achieves resonance. At this point, although the semantic dynamics are not yet fully resolved, the increasingly coherent system states will still distinguish PINT from legal nonwords, as indicated by the broken line that descends from BINT.

Eventually, visual–phonologic–semantic dynamics all settle into a coherent global resonance. This is indicated in Figure 6 in the outermost loop between PINT and *container filled with lager*. At this point, system states will distinguish PINT from pseudohomophones, as indicated by the broken line that descends from HEET. Of course, we do not claim knowledge of true semantic features. Although the illustrated gloss on meaning would suit our purpose in a model, it falls far short of characterizing meaning in word perception—indeed, there are no guarantees that the attractor point in a lexical decision would even correspond to a recognizable meaning. Consider, for example, a cognitive linguistic account in which a word’s meanings are described in a radial category structure specified in combinations of image schemas (e.g., see the case study of OVER in Lakoff, 1987). We find this scheme appealing because it translates naturally into an attractor topology of surface–semantic relations, and because it grounds meaning in the actual content of human experience (see Gibbs, 1994, in press; M. Johnson, 1987; Lakoff, 1987). Given such a topology, we

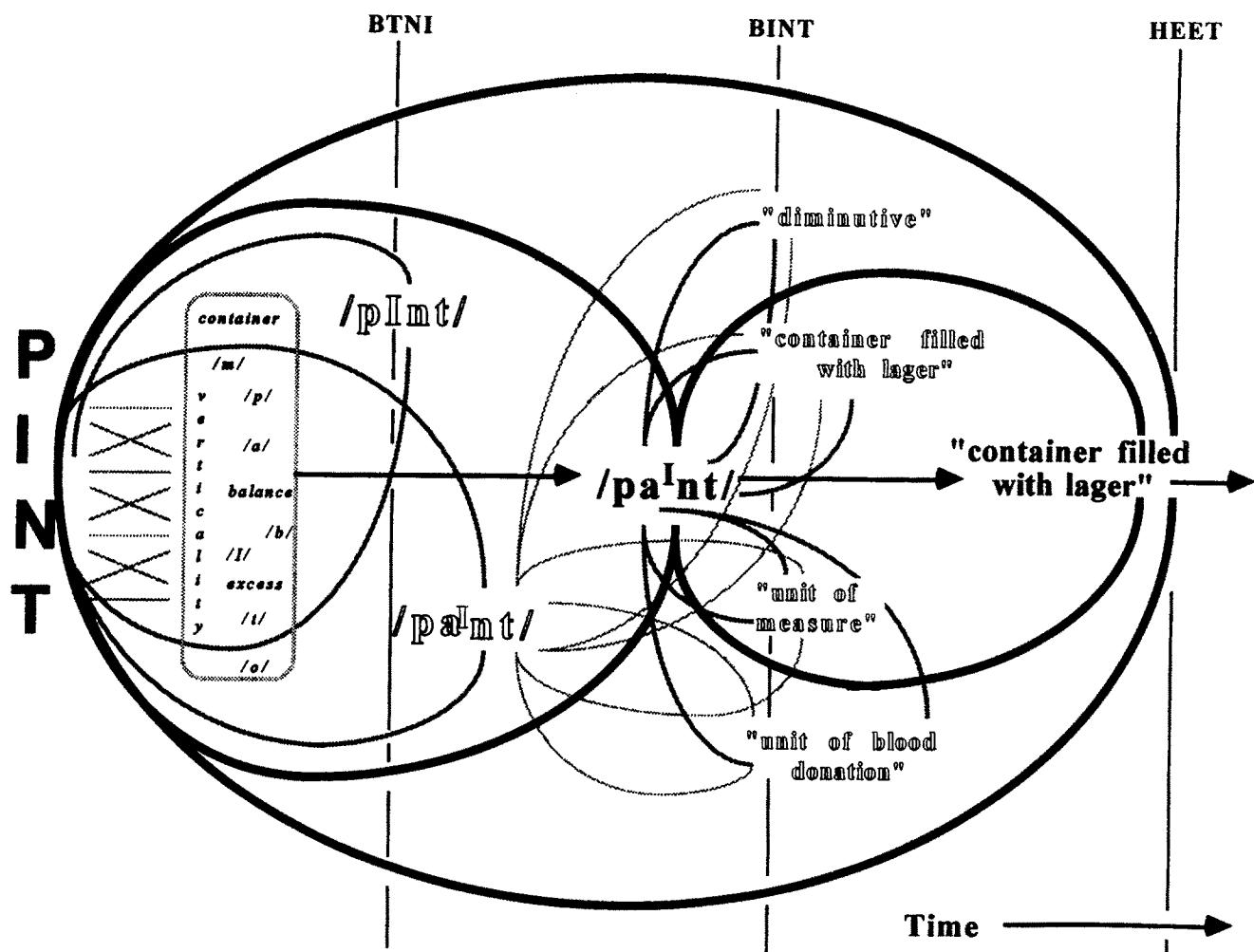


Figure 6. Perception of PINT as a trajectory through a hypothetical state space. Over time, cooperative-competitive dynamics evolve toward visual-phonologic, phonologic-semantic, and visual-semantic resonances.

could expect model dynamics to settle into "meaningful" attractor states consonant with active contextual constraints, but an isolated word in lexical decision could settle into an attractor state that reflects more the "central tendency" of learned meanings.

Figure 6 was constructed from a description of nested form-function correlations, discovered through fine-grain associative learning. These nested relations were then interpreted in terms of a general design principle—self-consistency. We chose to illustrate the word PINT because it shows interesting, competitive dynamics in its perceptual trajectory. The self-consistency principle, however, applies to all instances of word perception. We used it to explain mediating effects among spelling, phonology, and meaning; we applied it to complex patterns of data from the two major experimental tasks in word perception; and we followed its effects through the brief perceptual lifetime of a single word. In summary, covariant learning and self-consistency,

reflecting the interdependence of visual forms and linguistic functions, explain perception of printed words.

Word Perception and Reading

We began this article by noting how descriptions of complex systems have begun to shape theory in psychology (e.g., Engel, Konig, Kreiter, Gray, & Singer, 1991; Killeen, 1992; Skarda & Freeman, 1987; Smith & Sera, 1992; Thelen, 1989; Treffner & Turvey, 1993). The present account of word perception barely taps into this rich source of behavioral metaphors, however. Our requirements were met by simple neural networks tuned to cohere on fixed-point attractors. This relatively well-understood class of models helped us distill design principles. We also began by questioning whether componential theories may provide a satisfactory account of complex cognitive systems. In this re-

gard, our treatment of word perception in laboratory reading tasks requires several caveats.

One caveat derives from the complex behavior of neural network models. A neural network's behavior can appear very different, depending on how it is tuned to self-organize. A generic neural network, tuned to cohere on fixed-point attractors, emerges on the side of order and simplicity. However, the same network, tuned to strange (chaotic) attractors, will emerge on the side of disorder and idiosyncratic complexity. Between these extremes, at the "edge of chaos" (Langton, 1991, p. 36), a network will exhibit coherent behavior approaching, in complexity, our most detailed descriptions of natural systems. On the positive side, this range of complexity provides a rich set of metaphors for the complex behaviors confronted by cognitive scientists (e.g., Skarda & Freeman, 1987). Our concern, however, is that these qualitative changes in network behavior are produced by continuous changes in a single parameter (Langton, 1991). Thus, even "obvious" qualitative differences in behavior may not indicate discrete functional components, such as a separation of word perception from other aspects of reading.

A related caveat concerns the laboratory method used to study word perception. We have focused exclusively on aggregate data from word perception in laboratory reading tasks. Unlike spontaneous and continuous reading, our data were sampled in discrete trials and averaged across readers and words. These data describe perceptual events governed by a laboratory method that carefully limits temporal, spatial, and functional dimensions. Method inevitably reduces natural complexity to a narrow range, suitable for careful shared observation. Thus, our method carves out a discrete picture of behavior, but this laboratory perspective is conveniently isolated from the complexity of natural reading.

Of course, the full complexity of natural reading is only appreciated in private experience; we cannot directly observe the creative experience of another reader. Therein, the forms and functions of words are embedded in idiosyncratic experience (cf. Nagel, 1974). Extending William James's (1890/1950) metaphor, "slow-moving" reliable phenomena (e.g., coherent scientific discourse) emerge among "fast-moving" streams of consciousness. In private fast-moving experience, each interaction between a reader and text will be different—if only slightly—even for ostensibly identical reading events. In word perception, fine-grain constraints shape and are shaped by coarse-grain constraints. Likewise, word perception itself shapes and is shaped by the "fast moving" phenomenology of reading. Consequently, the form–function relations that predict laboratory performance may be correlated with natural reading, but they will not add up to its creative complexity. The trajectories of word perception may change in natural reading, conforming to its various added constraints.

The previous caveats derive from a point of view taken within a complex systems framework (a more inclusive framework than linear determinism). From our perspective, traditional componential explanations appear much less satisfying; "components of mind" are more clearly seen to be artifacts of method (see also Van Orden et al., 1994). This

does not diminish the utility of componential analyses for deriving first-order descriptions of data. In turn, however, first-order descriptions may be reframed in simple, general design principles. Such design principles apply equally to the fine-, intermediate-, and coarse-grain performance of word perception. Apparently, word perception is self-similar at all scales of observation. It is this prospect that is most exciting: To the extent that self-similarity applies, design principles ubiquitous in one behavioral domain could reappear in all behavioral domains. Hence, the principles of covariant learning and self-consistency may generalize far beyond word perception.

References

- Abraham, F. D., Abraham, R. H., & Shaw, C. D. (1991). *A visual introduction to dynamical systems theory for psychology*. Santa Cruz, CA: Aerial Press.
- Andrews, S. (1989). Frequency and neighborhood size effects on lexical access: Activation or search? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 15, 802–814.
- Andrews, S. (1992). Frequency and neighbourhood effects on lexical access: Lexical similarity or orthographic redundancy? *Journal of Experimental Psychology: Learning, Memory and Cognition*, 18, 234–254.
- Balota, D. A., & Chumbley, J. I. (1984). Are lexical decisions a good measure of lexical access? The role of word frequency in the decision stage. *Journal of Experimental Psychology: Human Perception and Performance*, 10, 340–357.
- Banks, W. P., Oka, E., & Shugerman, S. (1981). Recoding of printed words to internal speech: Does recoding come before lexical access? In O. J. L. Tzeng & H. Singer (Eds.), *Perception of print* (pp. 137–170). Hillsdale, NJ: Erlbaum.
- Bechtel, W., & Abrahamsen, A. A. (1991). *Connectionism and the mind: An introduction to parallel distributed processing*. Oxford, England: Basil Blackwell.
- Bechtel, W., & Richardson, R. C. (1993). *Discovering complexity: Decomposition and localization as strategies in scientific research*. Princeton, NJ: Princeton University Press.
- Becker, C. A. (1976). Allocation of attention during visual word recognition. *Journal of Experimental Psychology: Human Perception and Performance*, 2, 556–566.
- Berent, I., & Perfetti, C. A. (in press). A ROSE is a REEZ: The two cycles model of phonology assembly in English visual word recognition. *Psychological Review*.
- Besner, D., Twilley, L., McCann, R. S., & Seergobin, K. (1990). On the association between connectionism and data: Are a few words necessary? *Psychological Review*, 97, 432–446.
- Bosman, A. M. T. (1994). *Reading and spelling in children and adults: Evidence for a single-route model*. Unpublished doctoral dissertation, University of Amsterdam, The Netherlands.
- Carello, C., Turvey, M. T., & Lukatela, G. (1992). Can theories of word recognition remain stubbornly nonphonological? In R. Frost & L. Katz (Eds.), *Orthography, phonology, morphology, and meaning* (pp. 211–226). Amsterdam: North-Holland.
- Chomsky, N. (1965). *Aspects of the theory of syntax*. Cambridge, MA: MIT Press.
- Coltheart, M. (1978). Lexical access in simple reading tasks. In G. Underwood (Ed.), *Strategies in information processing* (pp. 151–216). San Diego, CA: Academic Press.
- Coltheart, M., Curtis, B., Atkins, P., & Haller, M. (1993). Models of reading aloud: Dual-route and parallel distributed processing approaches. *Psychological Review*, 100, 589–608.

- Coltheart, M., Davelaar, E., Jonasson, J. T., & Besner, D. (1977). Access to the internal lexicon. In S. Dornic (Ed.), *Attention and performance* (Vol. 6, pp. 535–555). Hillsdale, NJ: Erlbaum.
- Coltheart, V., Avons, S. E., Masterson, J., & Laxon, V. (1991). The role of assembled phonology in reading comprehension. *Memory & Cognition*, 19, 387–400.
- Dijkstra, T., Frauenfelder, U. H., & Schreuder, R. (1993). Bidirectional grapheme–phoneme activation in a bimodal detection task. *Journal of Experimental Psychology: Human Perception and Performance*, 19, 931–950.
- Donahue, J. W., & Palmer, D. C. (1989). The interpretation of complex human behavior: Some reactions to *Parallel Distributed Processing*, edited by J. L. McClelland, D. E. Rumelhart, & the PDP Research Group [Book review]. *Journal of the Experimental Analysis of Behavior*, 51, 399–416.
- Drewowski, A. (1981). Missing -ing in reading: Developmental changes in reading units. *Journal of Experimental Child Psychology*, 31, 154–158.
- Dunn, J. C., & Kirsner, K. (1988). Discovering functionally independent mental processes: The principle of reversed association. *Psychological Review*, 95, 91–101.
- Dunn, J. C., & Kirsner, K. (1989). Implicit memory: Task or process? In S. Lewandowsky, J. C. Dunn, & K. Kirsner (Eds.), *Implicit memory: Theoretical issues* (pp. 17–31). Hillsdale, NJ: Erlbaum.
- Engel, A. K., Konig, P., Kreiter, A. K., Gray, C. M., & Singer, W. (1991). Temporal coding by coherent oscillations as a potential solution to the binding problem: Physiological evidence. In H. G. Schuster (Ed.), *Nonlinear dynamics and neuronal networks* (pp. 3–25). New York: VCH Publishers.
- Farrar, W. T., & Van Orden, G. C. (1994). *BUSH can be TREE unless PINT rhymes with MINT: Simulated semantic and regularization errors in a recurrent neural network*. Unpublished manuscript.
- Fleming, K. K. (1993). Phonologically mediated priming in spoken and printed word recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 19, 272–284.
- Fodor, J. A. (1983). *The modularity of mind*. Cambridge, MA: MIT Press.
- Forster, K. I., & Chambers, S. M. (1973). Lexical access and naming time. *Journal of Verbal Learning and Verbal Behavior*, 12, 627–635.
- Fowler, C. A. (1989). Real objects of speech perception: A commentary on Diehl and Kluender. *Ecological Psychology*, 1, 145–160.
- Gibbs, R. W. (1994). *The poetics of mind: Figurative thought, language and understanding*. Cambridge, England: Cambridge University Press.
- Gibbs, R. W. (in press). What's cognitive about cognitive linguistics? In G. Casad (Ed.), *Cognitive linguistics in the redwoods*. The Hague, The Netherlands: Mouton.
- Gibson, J. J. (1950). *The perception of the visual world*. Boston: Houghton Mifflin.
- Gibson, J. J. (1966). *The senses considered as perceptual systems*. Boston: Houghton Mifflin.
- Gibson, J. J. (1971). *The problems of information pickup*. Unpublished manuscript.
- Gibson, J. J. (1986). *An ecological approach to visual perception*. Hillsdale, NJ: Erlbaum. (Original work published 1979)
- Gleick, J. (1987). *Chaos: Making a new science*. New York: Penguin Books.
- Glushko, R. (1979). The organization and activation of orthographic knowledge in reading aloud. *Journal of Experimental Psychology: Human Perception and Performance*, 5, 674–691.
- Goldinger, S. D. (1992). *Words and voices: Implicit and explicit memory for spoken words*. Unpublished doctoral dissertation, Indiana University.
- Goldinger, S. D., Pisoni, D. B., & Luce, P. A. (in press). Speech perception and spoken word recognition: Research and theory. In N. J. Lass (Ed.), *Principles of experimental phonetics*. St. Louis, MO: Mosby Year Book.
- Grainger, J., & Jacobs, A. M. (1993). Masked partial-word priming in visual word recognition: Effects of positional letter frequency. *Journal of Experimental Psychology: Human Perception and Performance*, 19, 951–964.
- Grainger, J., & Jacobs, A. M. (1994a). A dual read-out model of word context effects in letter perception: Further investigations of the word superiority effect. *Journal of Experimental Psychology: Human Perception and Performance*, 20, 1158–1176.
- Grainger, J., & Jacobs, A. M. (1994b). *A three-process model of lexical decision and word recognition*. Manuscript submitted for publication.
- Grainger, J., O'Regan, J. K., Jacobs, A. M., & Segui, J. (1989). On the role of competing word units in visual word recognition: The neighborhood frequency effect. *Perception & Psychophysics*, 45, 189–195.
- Grainger, J., O'Regan, J. K., Jacobs, A. M., & Segui, J. (1992). Neighborhood frequency effects and letter visibility in visual word recognition. *Perception & Psychophysics*, 51, 49–56.
- Grossberg, S. (1980). How does a brain build a cognitive code? *Psychological Review*, 87, 1–51.
- Grossberg, S. (1982). *Studies of mind and brain*. Dordrecht, The Netherlands: D. Reidel.
- Grossberg, S., & Stone, G. O. (1986). Neural dynamics of word recognition and recall: Priming, learning, and resonance. *Psychological Review*, 93, 46–74.
- Healy, A. F. (1976). Detection errors on the word *the*: Evidence for reading units larger than letters. *Journal of Experimental Psychology: Human Perception and Performance*, 2, 235–242.
- Hinton, G. E., & Sejnowski, T. J. (1986). Learning and relearning in Boltzmann machines. In D. E. Rumelhart & J. L. McClelland (Eds.), *Parallel distributed processing: Explorations in the microstructure of cognition: Vol. 1. Foundations* (pp. 282–317). Cambridge, MA: MIT Press.
- Hinton, G. E., & Shallice, T. (1991). Lesioning an attractor network: Investigations of acquired dyslexia. *Psychological Review*, 98, 74–95.
- Hunt, E., & Agnoli, F. (1991). The Whorfian hypothesis: A cognitive psychology perspective. *Psychological Review*, 98, 377–389.
- Jacobs, A. M., & Grainger, J. (1992). Testing a semistochastic variant of the interactive activation model in different word recognition experiments. *Journal of Experimental Psychology: Human Perception and Performance*, 18, 1174–1188.
- Jacoby, L. L. (1983). Perceptual enhancement: Persistent effects of an experience. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 9, 21–38.
- Jacoby, L. L., & Hayman, C. A. G. (1987). Specific visual transfer in word identification. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 13, 456–463.
- James, W. (1950). *The principles of psychology* (Vol. 1). New York: Dover. (Original work published 1890)
- Jared, D., McRae, K., & Seidenberg, M. S. (1990). The basis of consistency effects in word naming. *Journal of Memory and Language*, 29, 687–715.
- Jared, D., & Seidenberg, M. S. (1991). Does word identification in reading proceed from spelling to sound to meaning? *Journal of Experimental Psychology: General*, 120, 358–394.

- Jastrzembski, J. (1981). Multiple meanings, number of related meanings, frequency of occurrence, and the lexicon. *Cognitive Psychology*, 13, 278-305.
- Johnson, D. D., & Venezky, R. L. (1976). Models for predicting how adults pronounce vowel digraph spellings in unfamiliar words. *Visible Language*, 10, 257-268.
- Johnson, M. (1987). *The body in the mind: The bodily basis of meaning, imagination, and reason*. Chicago: University of Chicago Press.
- Kawamoto, A. H. (1988). Distributed representations of ambiguous words and their resolution in a connectionist network. In S. I. Small, G. W. Cottrell, & M. K. Tanenhaus (Eds.), *Lexical ambiguity resolution* (pp. 195-228). San Mateo, CA: Morgan Kaufman.
- Kawamoto, A. H. (1993). Non-linear dynamics in the resolution of lexical ambiguity: A parallel distributed processing account. *Journal of Memory and Language*, 32, 474-516.
- Kawamoto, A. H. (in press). One system or two to handle regulars and exceptions: How time-course of processing can inform this debate. In R. Corigan, G. Iverson, & S. D. Lima (Eds.), *The reality of linguistic rules*. Philadelphia, PA: John Benjamin.
- Kawamoto, A. H., Farrar, W. T., & Kello, C. T. (1994). When two meanings are better than one: Modeling the ambiguity advantage using a recurrent distributed network. *Journal of Experimental Psychology: Human Perception and Performance*, 20, 1233-1247.
- Kawamoto, A. H., & Kitzis, S. N. (1991). Time course of regular and irregular pronunciations. *Connection Science*, 3, 207-217.
- Kawamoto, A. H., & Zemblidge, J. (1992). Pronunciation of homographs. *Journal of Memory and Language*, 31, 349-374.
- Killeen, P. (1989). Behavior as a trajectory through a field of attractors. In J. R. Brink & C. R. Haden (Eds.), *The computer and the brain: Perspectives on human and artificial intelligence* (pp. 53-82). Amsterdam: Elsevier.
- Killeen, P. (1992). Mechanics of the animate. *Journal of the Experimental Analysis of Behavior*, 57, 429-463.
- Kohonen, T. (1988). *Self-organization and associative memory*. Berlin, Germany: Springer-Verlag.
- Lakoff, G. (1987). *Women, fire, and dangerous things: What categories reveal about the mind*. Chicago: University of Chicago Press.
- Langton, C. G. (1991). Computation at the edge of chaos: Phase transitions and emergent computation. In S. Forrest (Ed.), *Emergent computation* (pp. 12-37). Cambridge, MA: MIT Press.
- Lewenstein, M., & Nowak, A. (1989). Recognition with self-control in neural networks. *Physical Review A*, 40, 4652-4664.
- Liberman, A. M. (1991). Observations from the sidelines. *Reading and Writing: An Interdisciplinary Journal*, 3, 429-433.
- Llewellen, M. J., Goldinger, S. D., Pisoni, D. B., & Greene, B. G. (1993). Lexical familiarity and processing efficiency: Individual differences in naming, lexical decision, and semantic categorization. *Journal of Experimental Psychology: General*, 122, 316-330.
- Lombardo, T. J. (1987). *The reciprocity of perceiver and environment*. Hillsdale, NJ: Erlbaum.
- Lorenz, E. N. (1963). Deterministic non-periodic flow. *Journal of Atmospheric Science*, 20, 130-141.
- Lukatela, G., Lukatela, K., Carello, C., & Turvey, M. T. (1994). Effects of phonological ambiguity on naming words as a function of frequency and attention. Manuscript submitted for publication.
- Lukatela, G., & Turvey, M. T. (1994). Visual lexical access is initially phonological: 1. Evidence from associative priming by words, homophones, and pseudohomophones. *Journal of Experimental Psychology: General*, 123, 107-128.
- MacWhinney, B., & Leinbach, J. (1991). Implementations are not conceptualizations: Revising the verb learning model. *Cognition*, 40, 121-157.
- MacWhinney, B., Leinbach, J., Taraban, R., & McDonald, J. (1989). Language learning: Cues or rules? *Journal of Memory and Language*, 28, 255-277.
- Maddox, W. T., & Ashby, F. G. (1993). Comparing decision bound and exemplar models of categorization. *Perception & Psychophysics*, 53, 49-70.
- Mandler, G. (1985). *Cognitive psychology: An essay in cognitive science*. Hillsdale, NJ: Erlbaum.
- Massaro, D. W., & Cohen, M. M. (1994). Visual, orthographic, phonological, and lexical influences in reading. *Journal of Experimental Psychology: Human Perception and Performance*, 20, 1107-1128.
- McClelland, J. L., & Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception: Part 1. An account of basic findings. *Psychological Review*, 88, 375-407.
- Meyer, D., & Gutschera, K. D. (1975). *Orthographic versus phonemic processing of printed words*. Paper presented at the meeting of the Psychonomic Society, Denver, CO.
- Miyake, N. (1986). Constructive interaction and the iterative process of understanding. *Cognitive Science*, 10, 151-177.
- Morris, I. (Ed.). (1982). *American Heritage dictionary* (2nd college ed.). Boston, MA: Houghton Mifflin.
- Moses, L. J., & Flavell, J. H. (1990). Inferring false beliefs from actions and reactions. *Child Development*, 61, 929-945.
- Nagel, T. (1974). What is it like to be a bat? *Philosophical Review*, 83, 435-450.
- Nielson, C. S. (1991). *Phonology affects identification of high frequency printed words*. Unpublished undergraduate honors thesis. Honors College, Arizona State University, Tempe, AZ.
- Nielson, C. S., & Van Orden, G. C. (1992, April). *Phonology affects identification of high frequency printed words*. Presented at the meeting of the Western Psychological Association, Portland, OR.
- Nowak, A., Szamrej, J., & Latané, B. (1990). From private attitude to public opinion: A dynamic theory of social impact. *Psychological Review*, 97, 362-376.
- Paap, K. R., Newsome, S. L., McDonald, J. E., & Schvaneveldt, R. W. (1982). An activation-verification model for letter and word recognition: The word-superiority effect. *Psychological Review*, 89, 573-594.
- Paap, K. R., Noel, R. W., & Johansen, L. S. (1992). Dual-route models of print to sound: Red herrings and real horses. In R. Frost & L. Katz (Eds.), *Orthography, phonology, morphology, and meaning* (pp. 293-318). Amsterdam: North-Holland.
- Patterson, K. E., Seidenberg, M. S., & McClelland, J. L. (1989). Connections and disconnections: Acquired dyslexia in a computational model of reading processes. In R. G. M. Morris (Ed.), *Parallel distributed processing: Implications for psychology and neurobiology* (pp. 131-181). New York: Oxford University Press.
- Peitgen, H. O., Jürgens, H., & Saupe, D. (1992). *Chaos and fractals: New frontiers of science*. New York: Springer-Verlag.
- Perfetti, C. A., Zhang, S., & Berent, I. (1992). Reading in English and Chinese: Evidence for a "universal" phonological principle. In R. Frost & L. Katz (Eds.), *Orthography, phonology, morphology, and meaning* (pp. 227-248). Amsterdam: North-Holland.
- Peter, M., & Turvey, M. T. (in press). Phonological codes are early sources of constraint in visual semantic categorization. *Perception & Psychophysics*.

- Pinker, S., & Prince, A. (1988). On language and connectionism: Analysis of a parallel distributed processing model of language acquisition. *Cognition*, 28, 73–193.
- Plaut, D. C., & McClelland, J. L. (1993). Generalization with componential attractors: Word and nonword reading in an attractor network. In *Proceedings of the Cognitive Science Society* (pp. 824–829). Hillsdale, NJ: Erlbaum.
- Plaut, D. C., & Shallice, T. (in press). Deep dyslexia: A case study of connectionist neuropsychology. *Cognitive Neuropsychology*.
- Plunkett, K., & Marchman, V. (1991). U-shaped learning and frequency effects in a multilayered perception: Implications for child language acquisition. *Cognition*, 38, 43–102.
- Posner, M. I. (1978). *Chronometric explorations of mind*. Hillsdale, NJ: Erlbaum.
- Prigogine, I., & Stengers, I. (1984). *Order out of chaos: Man's new dialogue with nature*. New York: Bantam Books.
- Prinzmetal, W. (1981). Principles of feature integration in visual perception. *Perception & Psychophysics*, 30, 330–340.
- Prinzmetal, W. (1990). Neon colors illuminate reading units. *Journal of Experimental Psychology: Human Perception and Performance*, 16, 584–597.
- Prinzmetal, W., Hoffman, H., & Vest, K. (1991). Automatic processes in word perception: An analysis from illusory conjunctions. *Journal of Experimental Psychology: Human Perception and Performance*, 17, 902–923.
- Prinzmetal, W., & Keysar, B. (1989). A functional theory of illusory conjunctions and neon colors. *Journal of Experimental Psychology: General*, 118, 165–190.
- Prinzmetal, W., & Millis-Wright, M. (1984). Cognitive and linguistic factors affect visual feature integration. *Cognitive Psychology*, 16, 305–340.
- Prinzmetal, W., Treiman, R., & Rho, S. H. (1986). How to see a reading unit. *Journal of Memory and Language*, 25, 461–475.
- Putnam, H. (1981). *Reason, truth, and history*. Cambridge, England: Cambridge University Press.
- Putnam, H. (1990). *Realism with a human face*. Cambridge, MA: Harvard University Press.
- Rapp, B. C. (1992). The nature of sublexical orthographic organization: The bigram trough hypothesis examined. *Journal of Memory and Language*, 31, 33–53.
- Rosson, M. B. (1985). The interaction of pronunciation rules and lexical representations in reading aloud. *Memory & Cognition*, 13, 90–99.
- Rumelhart, D. E., & McClelland, J. L. (1986a). On learning the past tense of English verbs. In J. L. McClelland & D. E. Rumelhart (Eds.), *Parallel distributed processing: Explorations in the microstructure of cognition: Vol. 2. Psychological and biological models* (pp. 216–271). Cambridge, MA: MIT Press.
- Rumelhart, D. E., & McClelland, J. L. (1986b). PDP models and general issues in cognitive science. In D. E. Rumelhart & J. L. McClelland (Eds.), *Parallel distributed processing: Explorations in the microstructure of cognition: Vol. 1. Foundations* (pp. 110–149). Cambridge, MA: MIT Press.
- Ryder, R. J., & Pearson, D. D. (1980). Influence of type-to-token frequencies and final consonants on adults' internalization of vowel digraphs. *Journal of Educational Psychology*, 72, 618–624.
- Sanocki, T. (1987). Visual knowledge underlying letter perception: Font-specific, schematic tuning. *Journal of Experimental Psychology: Human Perception and Performance*, 13, 267–278.
- Seidenberg, M. S. (1987). Sublexical structures in visual word recognition: Access units or orthographic redundancy? In M. Coltheart (Ed.), *Attention and performance* (Vol. 12, pp. 245–263). Hillsdale, NJ: Erlbaum.
- Seidenberg, M. S. (1992). Beyond orthographic depth in reading: Equitable division of labor. In R. Frost & L. Katz (Eds.), *Orthography, phonology, morphology, and meaning* (pp. 85–118). Amsterdam: North-Holland.
- Seidenberg, M. S., & McClelland, J. L. (1989). A distributed, developmental model of word recognition and naming. *Psychological Review*, 96, 523–568.
- Seidenberg, M. S., Plaut, D. C., Petersen, A. S., McClelland, J. L., & McRae, K. (1994). Nonword pronunciation and models of word recognition. *Journal of Experimental Psychology: Human Perception and Performance*, 20, 1177–1196.
- Shepard, R. N. (1984). Ecological constraints on internal representation: Resonant kinematics of perceiving, imagining, thinking, and dreaming. *Psychological Review*, 91, 417–447.
- Shepard, R. N. (1989). Internal representation of universal regularities: A challenge for connectionism. In L. Nadel, L. A. Cooper, P. Culicover, & R. M. Harnish (Eds.), *Neural connections, mental computation* (pp. 104–134). Cambridge, MA: MIT Press.
- Skarda, C. A., & Freeman, W. J. (1987). How brains make chaos in order to make sense of the world. *Behavioral and Brain Sciences*, 10, 161–195.
- Smith, L. B., & Sera, M. D. (1992). A developmental analysis of the polar structure of dimensions. *Cognitive Psychology*, 24, 99–142.
- Smolensky, P. (1986a). Formal modeling of subsymbolic processes: An introduction to harmony theory. In N. E. Sharkey (Ed.), *Advances in cognitive science* (Vol. 1, pp. 204–235). New York: Wiley.
- Smolensky, P. (1986b). Information processing in dynamical systems: Foundations of harmony theory. In D. E. Rumelhart, J. L. McClelland, & The PDP Research Group, *Parallel distributed processing: Explorations in the microstructure of cognition: Vol. 1. Foundations* (pp. 194–281). Cambridge, MA: MIT Press.
- Sternberg, S. (1969). The discovery of processing stages: Extensions of Donders' method. *Acta Psychologica*, 30, 276–315.
- Stone, G. O., & Van Orden, G. C. (1989). Are words represented by nodes? *Memory & Cognition*, 17, 511–524.
- Stone, G. O., & Van Orden, G. C. (1993). Strategic processes in printed word recognition. *Journal of Experimental Psychology: Human Perception and Performance*, 19, 744–774.
- Stone, G. O., & Van Orden, G. C. (1994). Building a resonance framework for word recognition using design and systems principles. *Journal of Experimental Psychology: Human Perception and Performance*, 20, 1248–1268.
- Taraban, R., & McClelland, J. L. (1987). Conspiracy effects in word pronunciation. *Journal of Memory and Language*, 26, 608–631.
- Thelen, E. (1989). Self-organization in developmental processes: Can systems approaches work? In M. Gunnar (Ed.), *Systems in development: The Minnesota symposium in child psychology* (Vol. 22, pp. 77–117). Hillsdale, NJ: Erlbaum.
- Treffner, P. J., & Turvey, M. T. (1993). Resonance constraints on rhythmic movement. *Journal of Experimental Psychology: Human Perception and Performance*, 19, 1221–1237.
- Treisman, A. M., & Schmidt, H. (1982). Illusory conjunctions in the perception of objects. *Cognitive Psychology*, 14, 107–141.
- Turvey, M. T. (1977). Preliminaries to a theory of action with reference to vision. In R. Shaw & J. Bransford (Eds.), *Perceiving, acting, and knowing* (pp. 211–265). Hillsdale, NJ: Erlbaum.
- Turvey, M. T., & Carello, C. (1981). Cognition: The view from ecological realism. *Cognition*, 10, 313–321.

- Turvey, M. T., Shaw, R. E., Reed, E. S., & Mace, W. M. (1981). Ecological laws of perceiving and acting: In reply to Fodor and Pylyshyn (1981). *Cognition*, 9, 139-195.
- Uttal, W. R. (1990). On some two-way barriers between models and mechanisms. *Perception & Psychophysics*, 48, 188-203.
- van der Maas, H. L. J., & Molenaar, P. C. M. (1992). Stagewise cognitive development: An application of catastrophe theory. *Psychological Review*, 99, 395-417.
- Van Orden, G. C. (1987). A ROWS is a ROSE: Spelling, sound, and reading. *Memory & Cognition*, 15, 181-198.
- Van Orden, G. C. (1991). Phonologic mediation is fundamental to reading. In D. Besner & G. Humphreys (Eds.), *Basic processes in reading: Visual word recognition* (77-103). Hillsdale, NJ: Erlbaum.
- Van Orden, G. C., & Goldinger, S. D. (1994). *The interdependence of form and function in cognitive systems explains phonologic mediation in reading*. Unpublished manuscript.
- Van Orden, G. C., Johnston, J. C., & Hale, B. L. (1988). Word identification in reading proceeds from spelling to sound to meaning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14, 371-385.
- Van Orden, G. C., Pennington, B. F., & Stone, G. O. (1990). Word identification in reading and the promise of subsymbolic psycholinguistics. *Psychological Review*, 97, 488-522.
- Van Orden, G. C., Pennington, B. F., & Stone, G. O. (1994). What do double dissociations prove? Inductive logics and isolable systems. Manuscript submitted for publication.
- Van Orden, G. C., Stone, G. O., Garlington, K. L., Markson, L. R., Pinn, G. S., Simonfy, C. M., & Brichetto, T. (1992). "Assembled" phonology and reading: A case study in how theoretical perspective shapes empirical investigation. In R. Frost & L. Katz (Eds.), *Orthography, phonology, morphology, and meaning* (pp. 249-292). Amsterdam: North-Holland.
- Van Tuijl, H. F. J. M. (1975). A new visual illusion: Neonlike color spreading and complementary color induction between subjective contours. *Acta Psychologica*, 39, 441-445.
- Varela, F. J., Thompson, E., & Rosch, E. (1991). *The embodied mind: Cognitive science and human experience*. Cambridge, MA: MIT Press.
- Waters, G. S., & Seidenberg, M. S. (1985). Spelling-sound effects in reading: Time-course and decision criteria. *Memory & Cognition*, 13, 557-572.
- Wydell, T. N., Patterson, K. E., & Humphreys, G. W. (1993). Phonologically mediated access to meaning for Kanji: Is a Rows still a Rose in Japanese Kanji? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 19, 491-514.

Received January 31, 1994

Revision received April 1, 1994

Accepted April 15, 1994 ■

P&C Board Appoints Editor for New Journal: *Journal of Experimental Psychology: Applied*

In 1995, APA will begin publishing a new journal, the *Journal of Experimental Psychology: Applied*. Raymond S. Nickerson, PhD, has been appointed as editor. Starting immediately, manuscripts should be submitted to

Raymond S. Nickerson, PhD
Editor, *JEP: Applied*
Department of Psychology
Tufts University
Medford, MA 02155

The *Journal of Experimental Psychology: Applied* will publish original empirical investigations in experimental psychology that bridge practically oriented problems and psychological theory. The journal also will publish research aimed at developing and testing of models of cognitive processing or behavior in applied situations, including laboratory and field settings. Review articles will be considered for publication if they contribute significantly to important topics within applied experimental psychology.

Areas of interest include applications of perception, attention, decision making, reasoning, information processing, learning, and performance. Settings may be industrial (such as human-computer interface design), academic (such as intelligent computer-aided instruction), or consumer oriented (such as applications of text comprehension theory to the development or evaluation of product instructions).