Journal of Abnormal Psychology
1999, Vol. 108, No. 4, 633–654

0021-843X/99/$3.00

Cognitive Processing of Multidimensional Stimuli in Schizophrenia: Formal Modeling of Judgment Speed and Content

Jeffrey R. Carter and Richard W. J. Neufeld
University of Western Ontario

This article presents a formal, mathematical account of relations between response times on simple cognitive tasks and content of complex judgments involving multiple stimulus dimensions for people with schizophrenia. Changes in multidimensional judgments were viewed as the result of interference from increased stages of encoding with respect to the individual dimensions. Information on dimensional properties encoded earlier in a judgment trial was considered to be more susceptible to loss over the rest of the trial, because of a larger number of encoding stages applied to the remaining dimensional properties. Model predictions were tested with samples of paranoid and nonparanoid schizophrenic participants and controls. Unidimensional encoding speed was assessed by reaction times in an explicit similarity ratings task, and multidimensional judgment content was assessed by the relative importance of different stimulus dimensions to participants' ratings in an implicit similarity ratings task. Results support validity of the model.

The study of information processing in schizophrenia has yielded considerable material on abnormalities of memory and cognition (e.g., Cromwell & Snyder, 1993). Cognitive tasks on which abnormalities have been observed often have entailed the analyses of complex stimuli along multiple dimensions of relatedness. For example, people with schizophrenia have been found to be less likely to organize verbal stimuli according to memory-facilitative semantic proximities than controls (e.g., Koh, Kayton, & Berry, 1973). Samples of language behavior have also indicated diminished influence of latent semantic networks on sequences of words and phrases (Hoffman, Stopek, & Andreason, 1986). Reduced influence of stimulus dimensions has been evident in item-sorting test performance (e.g., Dobson & Neufeld, 1982), including that identified with frontal-cortex functioning (Paulman et al., 1990), categorization of facial emotions, and the judgment of similarity among words (Neufeld, 1976). The present work addresses sources of deficit in multidimensional judgments.

To this end, findings on deficits in encoding processes facilitating other cognitive operations were examined. Encoding processes have been found to entail more stages when carried out by schizophrenic patients, especially those of the paranoid subtype (reviewed in Neufeld & Williamson, 1996). Delays in encoding, in turn, have paralleled reduced organization of multidimensional stimuli (Broga & Neufeld, 1981a). In this article, we describe and evaluate a formal mathematical model integrating these parallel deficits.

Emphasis is placed on cognitive processes underlying judgment formation. Processes include the encoding of individual dimensions relevant to multidimensional judgments. They include, as well, retention of encoded dimensional properties pending response. In this study, participants were timed as they rated pairs of words and pairs of schematic faces in terms of both overall similarity and similarity on specific, predetermined dimensions. The model posits that memorial traces formed earlier in a judgment trial are vulnerable to retroactive interference from subsequent dimension completions, more so if encoding stages are increased as in schizophrenia. The more salient dimensions of interstimulus similarity are disproportionately affected because they tend to precede others in the train of dimension-encoding completions (as we discuss below). Unidimensional encoding speed was assessed by the reaction times on an explicit similarity ratings task, and multidimensional judgment content was assessed by the relative importance of different stimulus dimensions to participants' ratings on an implicit similarity ratings task.

There are many potential benefits of synthesizing molecular and molar cognitive-performance deficits. Parsimony is increased by theoretically unifying documented deviations in encoding simple stimuli or their features (where response latency is emphasized) with deviations in organizing complex stimuli (where response content/quality is emphasized). The resulting synthesis seemingly applies in a number of instances.

Prominent card- and object-sorting tasks, for example, involve the cognitive assembly of multiple stimulus dimensions in terms of an organizing principle (e.g., Pishkin & Bourne, 1981). Material encoded earlier during a given sorting trial is susceptible to interference from intervening encoding operations (Chechile, 1987),

Jeffrey R. Carter and Richard W. J. Neufeld, Department of Psychology, University of Western Ontario, London, Ontario, Canada.

Sources of support for this research included a doctoral fellowship from the Canadian Social Sciences and Humanities Research Council; an Ontario Graduate Scholarship; Ontario Mental Health Foundation and Tannenbaum-Scientist Research Fellowships; and operating grants from the Canadian Medical Research Council and U.S. National Institute of Mental Health. This article is based on a thesis by Jeffrey R. Carter that was supervised by Richard W. J. Neufeld and submitted in partial fulfillment of the requirements for the master's degree in clinical psychology at the University of Western Ontario. A portion of this work was presented in August 1996 at the 104th Annual Convention of the American Psychological Association, Toronto, Ontario, Canada. Thanks are extended to Peter Williamson for his comments on the findings.

Correspondence concerning this article should be addressed to Jeffrey R. Carter, Department of Psychology, University of Western Ontario, London, Ontario, Canada N6A 5C2.

with an increase in such operations jeopardizing the critical accumulation of information necessary to solve the problem (Dobson & Neufeld, 1982). This characterization may apply to sorting tasks considered sensitive to frontal-lobe integrity (e.g., the Wisconsin Card-Sorting and related tests). If so, then frontally located encoding deficits mediating an overall decline in performance may be implicated (e.g., elevated "perseveration errors" in card selection; Paulman et al., 1990).

The list of deficits in multidimensional tasks that may be affected by unidimensional encoding deficiency is extensive. Suffice it to say that such multidimensional transactions may bear on the negotiation of daily activities, ranging from mnemonic organization to resolution of environmental stressors (Neufeld, 1999a). Regarding symptomatology, incomplete multidimensional information may foster thought-content disorder (Neufeld, Vollick, & Highgate, 1993). Finally, mathematical models of cognitive psychopathology may inform, and be informed by, neuro-connectionist simulations (e.g., Hoffman et al., 1995).

This model description includes the essential features of the proposed model relating unidimensional-encoding speed to multidimensional-judgment quality. Quantitative developments bearing on the model's formal aspect are appendicized or are presented in cited technical reports. Tutorials on stochastic-process model applications are available elsewhere (e.g., Neufeld, 1998).

A verbal summary of the process model is presented in Table 1. Consider judgments comprising multidimensional semantic similarity of stimulus pairs. Such judgments assumedly depend on the similarity of the stimuli on individual dimensions (e.g., "potency," "desirability," "activity"). A common geometric expression of the judged dissimilarity, d, between a pair of stimuli, x_1 and x_2 (see Item H of Table 1), takes the following form (e.g., Schiffman, Reynolds, & Young, 1981):

$$d_{x_1x_2} = [\sum_{i=1}^{r} w_i(x_{1i} - x_{2i})^2]^{1/2}. \quad (1)$$

Here, x_{1i} and x_{2i} are the stimulus values on dimension i, while w_i is the weight of dimension i for an individual judge, reflecting the influence of that dimension on the judge's dissimilarity judgment. The source of schizophrenia multidimensional-judgment deficit is modeled with reference to Equation 1.

Stimulus values on individual dimensions x_{1i} and x_{2i}, as held in semantic memory, are assumed to be the same among schizophrenia and control participants (Neufeld, 1976). The relative influence of dimension i, w_i, when it comes to (dis)similarity judgment(s) d, however, is considered to be diminished among schizophrenia participants (Item H of Table 1). The source of this reduction can be appreciated by considering the make-up of w_i. This term is modeled as the product of the following two variables: (a) the intrinsic salience of dimension i, denoted m_i, and (b) the probability of survival of the memorial trace conveying the encoded separation on dimension i of the judged stimulus pair. That is, w_i is the expected value of m_i, or $E(m_i)$, which is the product m_i (*Probability of Survival of Trace i*); $i = 1, 2, \ldots, r$, where there are r dimensions. Like the stimulus values on dimension i, above, the intrinsic salience of semantic dimension i, m_i once again is considered to be the same for schizophrenia and control participants (e.g., Neufeld & Williamson, 1996). The source of deviation in values of w_i therefore involves the probability that the trace survives until needed for the judgment.

This probability is a function of the time between encoding the stimulus-pair with respect to dimension i and making the final judgment. The above interval following completion of dimension i is assumed to be occupied by encoding of still-uncompleted dimensions (see Figure 1). Because of the documented delay in encoding among schizophrenia participants, this interval is considered to be extended, making for increased risk of trace loss and reduced influence of dimension i on the ensuing multidimensional judgment.

Dynamic features of trace survival have been the subject of rigorous formal modeling in cognitive psychology (Chechile, 1987). Trajectories describing the probability of trace loss over

Table 1
Summary of Process Model of Multidimensional Judgments and Schizophrenia-Related Judgment Deviations

Item	Summary
A	Multidimensional judgments involve encoding of stimuli with respect to dimensional properties, which compose the judgmental response (e.g., the encoding of pairs of words with respect to component semantic dimensions, such as pleasantness, potency, and activation, which compose judgments of semantic similarity).
B	As the completion of the encoding process and the judgment response increasingly become separated by intervening cognitive events, there is a greater risk of loss of the memorial trace conveying earlier encoded dimensional information.
C	One source of increased separation between dimensional encoding completion and judgment consolidation is extended encoding of other dimensions still in progress.
D	As the number of subprocesses, or stages, involved in the encoding process increases, the number of subprocesses remaining to be transacted on an uncompleted dimension increases (whether dimensional processing proceeds in serial or in parallel; see Figure 1 and Appendix B).
E	Encoding of intrinsically more salient dimensions will be completed before those that are intrinsically less salient.
F	Thus, the risk of losing the memorial trace conveying dimensional properties will increase primarily with respect to dimensions that are intrinsically more salient, if the number of encoding subprocesses rises throughout; put differently, subsequent dimensional encoding will retroactively interfere with memorial traces of earlier encoded dimensions more than those of later encoded dimensions.
G	Encoding operations among schizophrenic participants are characterized by increased subprocesses that form an encoding process.
H	Considering F and G together, indexes of dimensional influence on judgment responses should tend to differ between schizophrenic participants and controls, especially for intrinsically more salient dimensions. Such indexes include dimension-salience weights of multidimensional scaling algorithms used to analyze similarity judgments, such as Individual Differences Multidimensional Scaling (INDSCAL; Carroll & Chang, 1970). Allowing the relative order of intrinsic dimensional salience to be inferred from empirical INDSCAL salience weights among controls, the aforementioned pattern of group differences across differentially salient dimensions has been observed (Neufeld, 1975, 1976).

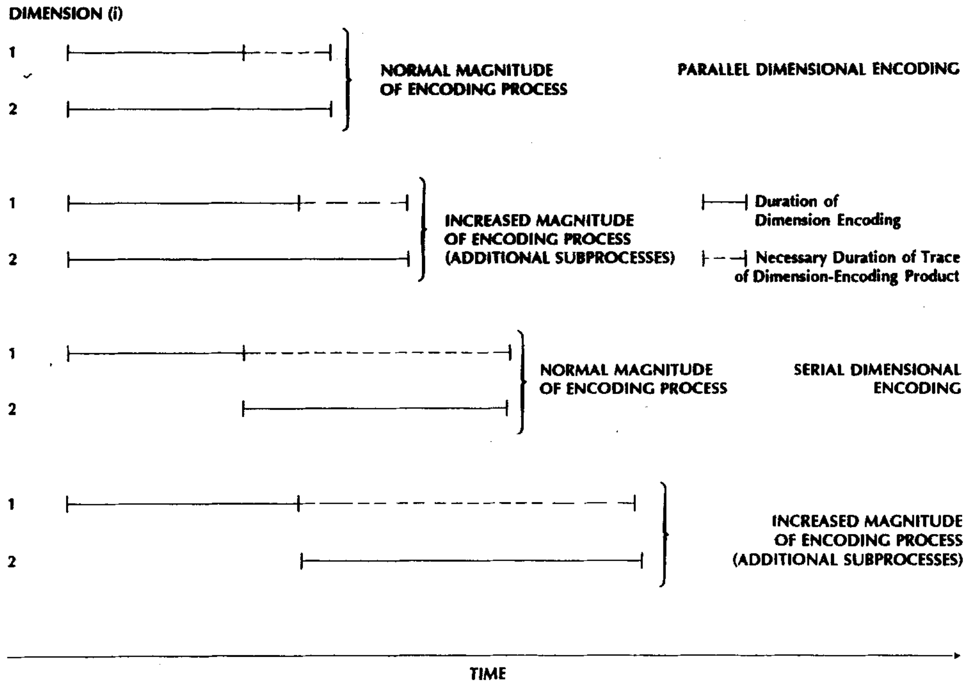

Figure 1. Schematic portrayal of encoding latencies for two dimensions processed in parallel (top half of figure) and in serial (bottom half). In each case, protracted finalization of dimensional encoding necessitates longer memorial retention of the first-completed dimension for that dimension to influence the judgment response.

time ("trace-survivor functions") can be depicted according to stochastic models of "event history"[1] (e.g., Galambos, 1978). Those potentially characterizing the path of trace loss in the present context are presented in Appendix A.

Each trace-survival expression $\bar{F}(t)$ has a specific architecture prescribed by an algebraic function $\bar{F}$ of time t, with associated parameters. These parameters (delineated in Appendix A) include the rate of trace disintegration and also allow for variations such as rehearsal, potential invulnerability of traces, and retrieval despite partial failure. The model architecture is regarded as being the same across groups of participants, as are its parameter values. The source of diminished values of $\bar{F}(t)$ therefore does not lie in the algebraic function $\bar{F}$ but in longer intercompletion times t to which the function is applied.

The source of increased t in turn comprises additional encoding subprocesses (Neufeld et al., 1993) applied to dimension(s) remaining to be dealt with (serial dimensional encoding) or to those still in progress (parallel encoding; Item D of Table 1). Cognitive–behavioral correlates of this source have been tendered elsewhere (Neufeld & Williamson, 1996). In the present instance, they tentatively entail additional steps involved in reading and cognitive representation, accessing the relation of each item to the similarity dimension being processed, comparing item positions, and ascertaining their dimensional distance. The additional covert steps potentially involve disengagement deficit, overinclusiveness, and orienting activity, among other sources (reviewed in Neufeld & Williamson, 1996). Note that the invocation of additional subprocesses as the source of increased t is compatible with the observation that the agent of trace loss is not the passage of time in and of itself, but the cognitive activities taking place in the interim (Chechile, 1987).

The amount of subprocesses outstanding for an uncompleted dimension is estimable from associated unidimensional encoding times. This statement applies to cases of serial or parallel encoding, for reasons described in Appendix B.

Overall, then, unidimensional encoding latency was used in conjunction with formal parametric survivor functions to predict salience weights of Equation 1 for paranoid and nonparanoid schizophrenic patients and controls. Specifically, the salience weights w_i of the second least salient dimension of judged words or faces were predicted using unidimensional encoding times of the stimulus set's least salient dimension (Item H of Table 1). Less salient dimensions are defensibly completed after more salient dimensions (see Appendix B; elaborated in Carter & Neufeld, 1996). Findings from complementary levels of performance therefore were embedded in mathematically sound parametric process models of cognition.

Method

Participants

Participants were 20 paranoid schizophrenic patients, 20 nonparanoid schizophrenic patients, and 20 controls. The present subgroup division was undertaken because (a) such division occurred in past research using similar judgments; (b) various premorbid and prognostic variables have

[1] Doob (1953) stated, "A stochastic model is the mathematical abstraction of an empirical process whose development is governed by probabilistic laws" (p. *v*). Rationale for the present selection of candidate functions is presented in Carter and Neufeld (1996), available from Richard W. J. Neufeld.

been associated with paranoid–nonparanoid symptomatology (see, e.g., Strauss, 1973); and (c) configurations of symptom intercorrelations are compatible with this division (Neufeld & Williamson, 1996). Nonpatient volunteers were recruited through Employment Canada (London, Ontario). All participants were between 18 and 60 years of age, had an educational level of Grade 8 or above, had no record of brain damage, and did not have current drug dependency or alcoholism included in their diagnosis. In addition, patients had fewer than 36 months cumulative hospitalization, no electroconvulsive therapy within the 6 months before testing, and an *International Classification of Diseases—10* clinical diagnosis of currently active schizophrenia. Participants were assigned to paranoid schizophrenic, nonparanoid schizophrenic, or nonschizophrenic groups by Research Diagnostic Criteria (RDC; Spitzer, Endicott, & Robins, 1978), by using information obtained from structured interview (Symptom-Sign Inventory [SSI]; Foulds, Caine, Adams, & Owen, 1965). In addition, diagnoses were corroborated by the Maine Scale of Paranoid and Nonparanoid Schizophrenia (Magaro, Abrams, & Cantrell, 1981), using the highest-subscale criterion (Lubow, Weiner, Schlossberg, & Baruch, 1987). Three patients were excluded from the analysis because their RDC diagnosis, Maine Scale scores, and clinical diagnoses were not in agreement, and one patient declined to complete the experiment. Two control participants were excluded because they met at least one RDC criterion for disorder. Each of these participants was replaced. Table 2 presents the demographic characteristics of the present samples.

Table 2
Demographic Characteristics of Groups

Characteristic	Group		
	Paranoid	Nonparanoid	Control
Age (years)			
M	37.95	42.30	30.55
SD	9.26	10.74	10.13
Handedness[a]			
M	0.63	0.53	0.69
SD	0.56	0.59	0.35
Gender			
Men	19	15	13
Women	1	5	7
WAIS-Clarke IQ[b]			
M	10.60	11.05	12.05
SD	2.11	2.30	1.49
Social class (Hollingshead)[c]			
M	3.65	3.60	3.25
SD	0.88	0.75	0.97
Social class (1981 Canadian census)[d]			
M	35.26	35.05	36.35
SD	13.40	8.76	12.31
Cumulative hospitalization (months)			
M	13.75	13.65	
SD	12.26	10.66	
Antipsychotic medication[e] (mg chlorpromazine equivalencies)			
M	502.20	618.31	
SD	768.22	470.52	
Anti-Parkinsonian medication[e] (mg benztropine equivalencies)			
M	1.42	1.35	
SD	1.53	1.48	

Note. WAIS = Weschler Adult Intelligence Scale.
[a] Edinburgh Handedness Index (Oldfield, 1971). [b] Paitich & Crawford (1970). [c] Hollingshead (1957) Two Factor Index of Social Position. [d] Blishen, Carroll, & Moore (1987). [e] Davis (1976); Krogh (1992); Wyatt & Torgow (1976).

Stimuli and Apparatus

Three sets of stimuli were used: two composed of words and one of schematic faces. One set of words consisted of 12 descriptors of affect, taken from Bush (1973). The second set of words was made up of 12 personality descriptors, adopted from Tucker (1972). Both sets have previously been used among the present types of samples (Neufeld, 1976). Schematic faces were obtained from "A Nonverbal Scale of Emotion," composed by Ridgeway and Russell (1985; cited in Lay, Waters, & Park, 1989). The faces were constructed to vary on two meaningful ordinal dimensions, "arousal" and "pleasure." These particular sets of stimuli were selected for generalizability across verbal and nonverbal domains, and because of their previously demonstrated complexity in terms of semantic dimensionality and their ecologically relevant content.

Stimuli were presented using slides and a rear projection screen. Participants sat approximately 85 cm from the screen. The front edge of the projector was 102 cm from the screen, producing characters up to 10 mm in height, and faces 65 mm in height. Visual angle between the midpoints and outer boundary of each member of a pair of stimuli was under 20 degrees. These display specifications accommodate the span of stimulus-intake among both nonchronic schizophrenic patients and controls (Cegalis, Leen, & Solomon, 1977). A Packard-Bell SX16 computer recorded responses and reaction times and advanced the slide projector. A London Research and Development 8254 Timer Board (London, Ontario, Canada) was used to measure response times in milliseconds.

Procedure

Overview. Participants completed the procedure in three stages. In the first stage, they answered the paper-and-pencil inventories and participated in a diagnostic interview. Next, they made judgments regarding the overall similarity of pairs of stimuli (implicit or multidimensional judgments). In the final stage, they judged the similarity of pairs of stimuli with reference to specific dimensions (explicit or unidimensional similarity judgments). Participants were timed for all judgments.

Multidimensional judgments. Participants were presented with all unique pairs of stimuli within each set (i.e., 66 for each of the verbal sets and 36 for the nonverbal set). There was a short break between sets (up to 5 min). The order of the sets, stimulus pairs within each set, and stimuli within pairs were balanced systematically. One third of the participants began with each of the three stimulus sets, each participant began at a different point within the set, and each word or schematic face was equally likely to be on the left or right for a given trial. On the basis of pilot testing, we allowed three practice judgments, using randomly selected pairs from the set at hand, to precede the recorded judgments. Participants indicated on a 9-point response panel the similarity of the items forming each pair, in terms either of facial expression or meaning. Anchors were *highly similar* (1) and *highly dissimilar* (9). The instructions were nondirectional, so as to preserve the symmetry assumption (i.e., the similarity of object *a* to *b* considered to be the same as *b* to *a*; Tversky, 1977).

The similarity judgments composed the data submitted to the multidimensional scaling algorithm. This algorithm deciphered the saliences (i.e., the contribution of each dimension to the overall-similarity judgment w_i) that later served in tests of model predictions. In addition, latencies of the multidimensional judgments were monitored throughout. These latencies were subsequently used to evaluate the tenability of assumptions regarding encoding processes involved in the broader trace-survival model of dimensional salience. Response latencies throughout were recorded as the duration, in milliseconds, from stimulus onset to response registration. This option was used in favor of allowing participants simply to indicate when a judgment had been made, followed by enunciation of its value; the option was deemed to risk fewer problems of "fast guessing" and postresponse processing (cf. Hughes, Reuter-Lorenz, Nozawa, & Fendrich, 1994).

Note that during both the present multidimensional judgments and the unidimensional judgments, described below, participants were not specifically paced in terms of instructions to respond as quickly and accurately as possible. Rather, participants were tacitly paced, inasmuch as recording of response time was apparent. This instructional milieu was in keeping with past conditions under which similar judgments were obtained (e.g., Neufeld, 1976).

Unidimensional judgments. After finishing the multidimensional judgments, and an additional break, participants undertook the unidimensional judgments. Thus, participants were not alerted to putative stimulus dimensions during their multidimensional judgments.

Twelve unique pairs of stimuli were selected from each of the three sets, for purposes of obtaining the relevant unidimensional judgments. Each subset of stimulus pairs, selected from its larger stimulus set, was determined by a procedure for representativeness presented by Spence and Domoney (1974), adapted to the present context (their Cyclic Design II). Participants again indicated, on a nine-point response panel, their interstimulus similarity assessments, this time with respect to the specific dimension under consideration. On the basis of pilot testing, we allowed three practice trials to precede the recorded judgments. Order of sets, pairs within sets, and items within pairs were varied as in the multidimensional judgments. A title slide before presentation of each set explicitly labeled the dimension along which the stimuli were to be judged. In addition, the meaning of each label was clarified verbally as necessary. Previous ratings of individual items composing each set of words along their respective dimensions of semantic similarity have been comparable across samples from the present populations of schizophrenic subgroups and controls, indicating the availability of each dimension in semantic memory (Neufeld, 1976).

Dimension labels for the affect descriptors were based on previous multidimensional scaling (MDS) results from paranoid and nonparanoid schizophrenic subtypes and controls, resembling the present samples (Neufeld, 1976). These dimension labels included "pleasant–unpleasant," "level of activation," and "aggression–activation." For the personality descriptors, dimension labels were designated in a similar fashion. Labels included "weak–strong," and "excitability." Finally, the schematic-face stimuli had been constructed to vary along the two dimensions, "pleasure," and "arousal" (cf. Lay, Waters, & Park, 1989), used for the unidimensional judgments.

Latencies for the unidimensional judgments served in the assessment of predictions regarding relations between unidimensional encoding speed and MDS dimension-salience weights. They were used as well in conjunction with the multidimensional similarity-judgment latencies, to assess the plausibility of inferred dimension-encoding processes.

Analytical Methods

Model testing procedures entailed standard methods for estimation of parameter values and testing of model predictions against empirical observations (see, e.g., Bamber & van Santen, 1985). Parameter estimation used maximum-likelihood criteria, whereby parameter values are those most probable in the population, given the structure of the mathematical model, and the data at hand (see Likelihood Ratio χ^2 of Appendix C). Minimum Pearsonian χ^2 (see Pearsonian χ^2 of Appendix C) was an alternate estimation criterion. The versatile function-maximizing algorithm, STEPIT 7.4 (Chandler, 1975), was used for parameter estimation and computation of G^2 (with associated degrees of freedom), a statistic that is asymptotically χ^2 with increasing response-sample size (Appendix C). Suggestions for avoiding suboptimal fit and imprecise parameter values, put forth by Piotrowski (1983), were used.

Estimation-and-test procedures were applied to both the response latency data from the unidimensional and multidimensional judgments (used to evaluate the plausibility of inferred encoding processes) and the broader model relating unidimensional encoding latency to MDS dimension-salience weights. Alternate trace-survivor functions (see Appendix A) serving in the broader model were examined, with the principle aim of implementing the simplest function allowing an adequate empirical fit (see, e.g., Grünwald, in press). Accuracy of predictions from competing models were compared with those of the proposed model. Several subsidiary analyses were undertaken to evaluate alternate aspects of model adequacy and validity of results.

Analysis of the multidimensional similarity judgments used the Individual Differences Multidimensional Scaling (INDSCAL) algorithm as implemented by the SPSS-X, Version 4.1 program, ALSCAL (Alternate Least Squares Scaling; Young, Takane, & Lewyckyi, 1988). The INDSCAL model and algorithm had been used in previous analyses informing the current work (Neufeld, 1976). Technical details of the algorithm have been provided elsewhere (Carroll & Arabie, 1980). INDSCAL provides stimulus values for each dimension used by the participants at large as well as a set of weights for each participant indicating the contribution of each respective dimension to his or her set of judgments (see Equation 1).

This program uses an iterative least-squares solution for the stimulus values and participants' weights to maximize the fit of the judgments computed from the weighted dimensions to the appropriately transformed (scalar products) original judgments (see Torgerson, 1958). The analysis solves for the stimulus coordinates and participants' weights in a multidimensional geometric space according to the number of orthogonal dimensions (solution dimensionality) specified by the user. Note that the method's participant-wise level of analysis avoids an inappropriate model fit when essential axioms regarding data properties in MDS have been violated (Ashby, Maddox, & Lee, 1994), and, like three-way factor analysis, creates a solution that is unique and cannot be rotated (Carroll & Chang, 1970). In summary, the analysis provides the stimulus values for each dimension of each solution and the relation of each solution's computed dimensions to each participant's judgments.

Results

Steps to critical tests of the proposed model relating response content and latencies proceed as follows: After a comparison of groups on demographic variables, tenability of the encoding processes proposed by the model is addressed. Toward this end, latency data were tested against predictions from model structures compatible with such processes. Next, results of a multidimensional scaling analysis of the content of the judgments are presented. The critical tests of the proposed model are followed by several additional analyses bearing on validity. This section concludes with a discussion of the functions most likely to describe accurately the relationship between response latency on unidimensional judgments and response content on multidimensional judgments.

Groups did not differ with respect to any of the shared demographic measures listed in Table 2, exceptions being age and gender ($p < .05$). The patient groups did not differ from one another in age, but each was significantly older than the control group (Newman-Keuls $p < .05$). Regarding gender, tests of separate 2×2 contingency tables indicated that the paranoid subgroup was the source of inequality. Pursuant to these results, correlational analyses were undertaken to estimate relations between age and gender, as well as patient-specific variables (hospitalization, antipsychotic and anti-Parkinsonian medication) and each dependent variable used in subsequent analyses. In no instance was a significant association obtained (procedures for multiple tests on correlations based on Larzelere & Mulaik, 1977); alpha was set at .10, two-tailed, per family of tests per group, like procedures being applied additionally to pooled intragroup correlations (e.g., Baggaley, 1964) involving patient specific variables. In the case of possible dependent-variable associations with gender, two-tailed t tests used Welch's adjustment for degrees of freedom involving unequal sample sizes; as well, it was ascertained that differing within-group variances did not combine with inequalities in sample size to create a negative statistical bias (Meyers & Well, 1993, pp. 105–109).

Tenability of Encoding Processes

The proposed model relies on two critical assumptions. First, people complete encoding operations for each individual stimulus dimension. Whether these operations proceed in parallel or in serial does not influence the potential validity of the proposed model.[2] Second, the proposed model assumes that processing of more salient dimensions tends to be completed before that of less salient dimensions. If encoded in serial, dimensions simply are deemed to be undertaken in order of salience, as indicated above. In the case of parallel processing, the more likely candidate of the two architectures (Torgerson, 1965), completion of dimension encoding again is considered to be ordered on salience (Appendix B). The analytical aspects of probing this assumption, however, are more involved. They include the construction and testing of a parallel encoding model expressing the posited order of completion.

In the parallel case, the probability of the more salient dimension being completed before the less salient dimension was arbitrarily required to be $\geq .99$. As completion order is a function of relative processing rates of the respective dimensions (their rates of subprocess transaction; Appendix B), it was necessary to establish the comparative values of these rates that would generate the designated probability regarding the order of completion. The requisite ratio of rates can be shown to vary with the number of encoding subprocesses involved. Hence, estimates of this number were required beforehand. Such estimates were available from unidimensional encoding latencies, where judgments were made on specific dimensions specified. With the subprocess estimates in hand, the required ratio of processing rates was implemented in a model of judgment latencies where constituent dimensions were denoted as being processed in parallel. Model predictions then were evaluated against empirical multidimensional processing latencies.

Estimating relative number of encoding subprocesses: Unidimensional judgments. Unidimensional judgments were represented in terms of an ordinary gamma distribution (see Appendixes A and B). The encoding-rate parameter u of this distribution initially was set equal to 1.0 throughout. This parameter is identified with "dimension salience" (Appendix B; Carter & Neufeld, 1996). The value of 1.0 was assigned because in the case of these unidimensional judgments, dimension salience was assumed to be equalized across dimensions and groups; the specific dimension under consideration was made explicit to each participant at the outset. The value of 1.0, moreover, conveniently is accordant with the maximum possible dimension-salience value w_i in the INDSCAL MDS algorithm.

The predicted encoding latency based on the ordinary gamma distribution was k/u. Here, k is the number of encoding subprocesses (presently to be estimated), and u is the rate of subprocess completion, set equal to 1.0 in the current case. The model prediction of response-time variability across trials, quantified as the standard deviation, was $(k/u^2)^{1/2}$. Parameter estimation of k, one value for each group and each dimension, was carried out by minimizing Equation C1, presented in Appendix C.

This procedure for parameter estimation was administered separately for each dimension, making for three estimates of k per dimension, one per group. Observations numbered six for each dimension, one mean and standard deviation for each of the three groups. The means and standard deviations serving as the observed values comprised the averages taken across participants within a group. In this way, each group was represented as a "homogeneous subject"; the use of standard deviations within this data-summary format can add considerably to efficiency of parameter estimation (Townsend, 1984).

Prior to aggregating data across participants, it was ascertained that individual means and, separately, standard deviations, could be viewed as representing observations from a single normally distributed population. Kolmogorov-Smirnov tests were applied to each group of aggregated values. (A significant result indicates that this assumption has been violated.) All tests were nonsignificant, with p values ranging from .169 to .999, and a mean of .735. Data aggregation, then, as undertaken here was an ideal tack to reducing error variance that would obscure the parameter values of a common model structure (Neufeld & Gardner, 1990).

For all analyses, an adjustment of the observed data was made for response movement time (e.g., Smith, 1995). Specifically, 160 ms were subtracted from each mean, and $(36 \text{ ms})^2$ from each variance (see, e.g., Townsend, 1984). Observe that the present response paradigm involved more than a simple button press or finger lift. Therefore, the possibility that the aforementioned values were underestimates of contribution to latencies from residual components is examined below.

Alternate versions of the present model included (a) releasing u to be a free parameter, rather than fixing it at 1.0; (b) fixing k equal to 1.0 and allowing u to vary across groups; and (c) releasing k as a free parameter as well as allowing u to vary across groups. Despite additional free parameters in versions (a) and (c), none of these variations led to meaningful improvement in fit over that where u was set at 1.0 and k was permitted to vary across groups. Also, variation (a) did not contraindicate the essential configuration of values of k presented in Tables 3 and 4, which varied across all stimulus sets as expected. Note further, regarding versions (b) and (c), that parameters with integer values, such as k, can be at a disadvantage regarding fine-tuning of model predictions relative to parameters whose values are continuous, such as u.

Multidimensional-encoding model structure and encoding rates. Turning to the multidimensional judgments, processing latencies were predicted using two models with competing structures: an independent parallel model, expressed as a simultaneous gamma process, and a serial model, expressed as an ordinary gamma process (Appendixes A and B). The simultaneous gamma process comprised an elaboration of Equation B2 of Appendix B, allowing for the modeling of means and standard deviations of latencies (detailed in Townsend, 1984). The ordinary gamma distribution, expressing serial processing, assumed that dimensions were en-

[2] A reviewer's suggestion of an alternate class of models in which judgments are completed by a global matching process (as in certain recognition models) highlights the importance of demonstrating that at least one of these model structures is viable.

Table 3
Means of Unidimensional Judgment Latencies (Interparticipant Standard Deviations in Parentheses), Average Intertrial Variability, and Model Predictions and Estimates (Two-Dimensional Item-Sets)

Dimension	Group	Observed mean latency, adjusted	Model-predicted mean latency	Observed variability	Model-predicted variability	Estimated k	$\hat{\chi}^2_{(df=3)}$
Faces							
Pleasure	Control	5.25 (2.68)	5	2.22 (1.86)	2.23	5	
	Paranoid schizophrenic	5.42 (2.79)	6	3.45 (2.00)	2.45	6	0.52
	Nonparanoid schizophrenic	5.24 (2.94)	6	2.92 (1.89)	2.45	6	
Arousal	Control	5.09 (2.64)	5	2.67 (1.71)	2.23	5	
	Paranoid schizophrenic	5.93 (2.97)	6	3.22 (2.15)	2.45	6	0.46
	Nonparanoid schizophrenic	5.58 (2.94)	6	3.23 (1.88)	2.45	6	
Personality descriptors							
Weak–Strong	Control	5.94 (2.39)	6	2.54 (1.31)	2.45	6	
	Paranoid schizophrenic	7.02 (3.19)	8	4.22 (1.97)	2.82	8	1.17
	Nonparanoid schizophrenic	6.81 (3.37)	8	4.00 (2.39)	2.82	8	
Excitability	Control	5.92 (2.36)	6	2.83 (1.53)	2.45	6	
	Paranoid schizophrenic	6.83 (2.74)	8	4.03 (1.51)	2.82	8	1.38
	Nonparanoid schizophrenic	7.10 (2.45)	8	4.43 (1.71)	2.82	8	

Note. Observed variability includes *SD* across judgment trials, adjusted.

coded in sequence, one after the other.[3] Parameters of this distribution were the processing rate u, and k, whose assigned value was the sum of the estimated subprocesses for the dimensions involved in the item set. Computational constraints dictated that only stimulus sets with two dimensions (faces and personality descriptors) be included.

Before embarking on estimation-and-test procedures and model comparisons for the multidimensional judgments, computer computations were used to establish the ratio of encoding rates, u_a to u_b, to be assigned to processes a and b of the simultaneous gamma model representing the parallel-processing hypothesis. Recall that it was required that the probability of completing the more salient dimension of each set first ("pleasure" for the face stimuli, and "weak–strong" for the word stimuli) be at least 0.99, given the current estimates of k (Appendix B; Carter & Neufeld, 1996). The obtained ratio for the schematic face stimuli was 4.5 and that for the personality descriptors was 4.0.[4] For each of these two sets of stimuli, therefore, a single parameter was estimated, specifically u_b, with u_a being set to 4.5 or 4.0 times u_b. The ratios of rate values, thus established for each set of stimuli, were applied to each group alike, making for two parameter estimates in all. Similarly, for the serial model, two estimates of the parameter u were obtained, one for each stimulus set. Note that the current constraints on structure and parameter relations would strain the predictive accuracy even of a potentially valid model (Townsend & Ashby, 1983, p. 156).

In estimating parameters and testing model fit, χ^2, presented in Equation C2 of Appendix C, was used (with $df = 4$), as specified in the appendix. Values of u_b (or simply u for the serial model) were estimated by minimizing Equation C2. In the first instance, observed variances in response latencies across multidimensional judgments within participants were introduced as values of Var_q in Equation C2. The latter was then minimized to obtain the two estimates of u_b. These values were inserted along with the earlier-established values of k into the theoretical (i.e., modeled-predicted) variance expression as specified by the simultaneous-gamma model. As an additional check on model fit, the resulting values for Var_q were then inserted into Equation C2. Both the χ^2 employing the observed-variance values and that employing their model-predicted variance replacements were tested for significance (see, e.g., Snodgrass & Townsend, 1980).

Next, the model-predicted variance expression (rather than the observed value) determined the Var_q terms of Equation C2. The to-be-estimated parameters u_b and the earlier-established values of k were inserted into this expression. In other words, the (preset) values for k and the free parameters u_b now appeared in both the simultaneous-gamma model-predicted means and the model-predicted Var_q's occurring in Equation C2. The latter equation once again was minimized and the resulting values of u_b were retained for entry into the model-predicted means in the further test of model fit. This time, however, observed variances replaced the model-specified variances as the Var_q terms in Equation C2, rather than the other way around. Once more, the initially minimized χ^2 as well as that with the replacement (observed) variances were tested for significance.

Before averaging observed data across participants within groups, Komogorov-Smirnov tests were applied to ascertain that aggregated means and, separately, standard deviations, were from a single normally distributed population. Prior to all computations, a "movement-time component" of 160 ms was subtracted from each observed mean, and $(36\text{ ms})^2$ from each observed variance.

[3] The ordinary gamma model is not confined to expressing a serial process. The model could depict a parallel process with capacity reallocation: upon completing one dimension, released encoding resources hypothetically are dealt to the remaining dimension. The rate of subprocess completion, in this case, can be shown to remain constant throughout the judgment trial, resulting in an ordinary gamma process.

[4] Given the simultaneous-gamma parallel model, the appropriated values of k, and the imposed ratios of u_a/u_b, the mean residual subprocesses of process b following completion of process a was 4.70, with a standard deviation of 1.20, among the paranoid and nonparanoid schizophrenia patients for the schematic-face stimuli, and 3.94, with a standard deviation of 1.06, among the controls. For the personality descriptors, the corresponding means were 6.02 and 4.56, with standard deviations of 1.53 and 1.26, respectively.

Table 4
Means of Unidimensional Judgment Latencies (Interparticipant Standard Deviations in Parentheses), Average Intertrial Variability, and Model Predictions and Estimates (Three-Dimensional Item-Set)

Dimension	Group	Observed mean latency, adjusted	Model-predicted mean latency	Observed variability	Model-predicted variability	Estimated k	$\hat{\chi}^2_{(\hat{df}=3)}$
Affect descriptors							
Pleasant–unpleasant	Control	5.76 (2.67)	6	2.78 (1.67)	2.45	6	
	Paranoid schizophrenic	7.44 (4.01)	8	4.15 (2.15)	2.82	8	0.766
	Nonparanoid schizophrenic	6.52 (2.93)	7	3.54 (1.64)	2.65	7	
Level of activation	Control	6.07 (2.78)	6	2.92 (1.67)	2.45	6	
	Paranoid schizophrenic	6.65 (2.71)	7	3.86 (1.67)	2.65	7	0.87
	Nonparanoid schizophrenic	7.26 (3.13)	8	3.95 (1.89)	2.82	8	
Aggression–activation	Control	6.05 (2.72)	6	2.79 (1.86)	2.45	6	
	Paranoid schizophrenic	7.09 (3.27)	8	3.69 (1.92)	2.82	8	1.16
	Nonparanoid schizophrenic	7.43 (2.53)	8	4.56 (2.28)	2.82	8	

Note. Observed variability includes *SD* across judgment trials, adjusted.

All Kolmogorov-Smirnov tests were nonsignificant, with p values ranging from .172 to .996, and a mean of 0.684.

For the parallel model, computed parameter values were highly similar, whether the model-predicted or observed variance terms served in the estimation procedure. Values of u_b were .95 and .96, respectively, in the case of face stimuli, and 1.19 and 1.18, for the personality descriptors. Also, in both instances, computed χ^2 values were similar. That obtained using the observed variance in the estimation procedure was 6.215, $p \approx 0.18$. Subsequently inserting the associated model-predicted variance resulted in a χ^2 of 9.17, $p \approx 0.06$. Initial estimation using the model-predicted variance resulted in a χ^2 of 9.047, $p \approx 0.06$. Replacing the model-predicted with the observed variance term produced a value of 6.304, $p \approx 0.18$.

The serial model structure on the whole generated less tractable and worse fitting solutions. Parameter estimation employing observed variances led to rate values of 1.925 for face stimuli and 2.35 for the personality descriptors. A value of 6.275 was obtained for χ^2, $p \approx 0.18$. However, the value was raised to 18.649, $p < 0.001$, when modeled variances were used, incorporating the above estimates of processing rate. Initial parameter estimates using modeled variances led to unreasonable rate values that tended to infinity. When the above values of 1.925 and 2.35 were specified as starting amounts, however, the estimation procedure remained stable at essentially these values. Table 5 lists observed data and model predictions.

Subsidiary analyses probed certain variations on the current parallel model. Both u_a and u_b were allowed to vary freely (u_a, u_b > 0), rather than requiring u_a to be scaled to u_b. Such alteration did not produce a superior model fit. Observe that this reduction in parameter constraints permitted a probability of less than 0.99 that the more salient dimension would be completed first.

Assumptions regarding the residual time component also were examined. Additional analyses assessed whether incorporating a residual-process time component as a free parameter would add to predictive accuracy. Unadjusted observed means and variances were used in the estimation-and-test procedures, discussed above, and a residual-time parameter t_{res} was added to the model predictions of means. In each instance of estimation, the value of t_{res} tended to become very small, not unlike the value previously assigned, with essentially no reduction in χ^2s occurring despite the additional free parameter.

In summary, results tended to support the independent parallel model of dimension encoding over the serial competitor. Despite

Table 5
Means of Multidimensional Judgment Latencies (Interparticipant Standard Deviations in Parentheses), Intertrial Variability, and Model Predictions

			Model-predicted mean latency			Model-predicted variability	
Stimulus set	Group	Observed mean latency, adjusted	Parallel model	Serial model	Observed variability	Parallel model	Serial model
Faces	Control	5.9572 (3.0791)	5.2688	5.1948	2.6910 (1.4962)	2.3456	1.6427
	Paranoid schizophrenic	6.1124 (2.7293)	6.3190	6.2338	3.5767 (1.7874)	2.5732	1.7995
	Nonparanoid schizophrenic	5.5603 (2.3240)	6.3190	6.2338	2.9133 (1.5554)	2.5732	1.7995
Personality descriptors	Control	5.3457 (2.1992)	5.0466	5.1064	2.7500 (1.4350)	2.0512	1.4741
	Paranoid schizophrenic	6.4084 (2.2097)	6.7245	6.8085	3.8738 (1.1469)	2.3736	1.7021
	Nonparanoid schizophrenic	6.6933 (2.2085)	6.7245	6.8085	4.1089 (1.4344)	2.3736	1.7021
Affect descriptors	Control	5.2341 (2.4934)			2.6912 (1.3038)		
	Paranoid schizophrenic	6.7337 (2.7153)			4.1841 (1.6559)		
	Nonparanoid schizophrenic	6.7608 (2.3301)			4.0484 (1.5184)		

Note. Observed variability includes *SD* across judgment trials, adjusted.

substantial constraints imposed on the first model structure, residual variance of predicted observations fell short of significance, or "well short" of significance. Qualitatively, a parallel encoding structure is in keeping with the Euclidean distance function depicting the present multidimensional judgments (Torgerson, 1965). It also is accordant with the observation that the mean latency and variability of the multidimensional judgments in some instances were lower than they were for their unidimensional counterparts (Townsend & Ashby, 1983, chap. 4). On balance, results favored a parallel architecture of dimension encoding and tenability of the assumed dimension-completion order. Although parallel processing seemed to be in effect, serial processing cannot be ruled out categorically. There exist serial processing models that can produce performance patterns empirically equivalent to those of the parallel model. Owing to space constraints, details are left to the original source (Townsend & Ashby, 1983, chap. 14).

The observation of lower latencies for some multidimensional as compared with unidimensional judgments implies that processing speed increased with an increase in task load. An increase in the rate of processing transaction under such conditions represents a case of "supercapacity."[5] Supercapacity can be produced by more than one type of processing mechanism (Townsend & Nozawa, 1995). Given a simultaneous-gamma process in the present case, the operative mechanism is considered to comprise cross-channel activation, whereby processing rates of the respective gammas can be enhanced. Formal expressions of this mechanism, transcending simultaneous gamma processes, are presented in the above sources. Empirical support for its theoretical extension to information processing under stress has been provided by Neufeld (1999b).

Finally, there is a pattern in Tables 3, 4, and 5 for the observed variability in latencies (standard deviations across judgment trials) to be smaller among the control participants. Reduced variability accompanying reduced means is not uncommon in the present type of information processing and is accommodated by tenable processing models (cf. Ashby, 1982). The present models are no exception, as indicated by the associated pattern of decline in model-predicted variability.

Multidimensional Scaling

The probabilities of memory traces surviving could not be observed directly and were instead derived from the calculated dimension weights and estimated intrinsic saliences. In the notation described above, for dimension i and judge j, $Pr(Survival\ of\ Trace\ ij) = w_{ij}/m_i$. The values of w_{ij} were taken directly from an INDSCAL analysis. The technical details of this analysis are as follows.

Initial configurations of stimulus values for personality and affect descriptors submitted to the ALSCAL algorithm conformed to those of Neufeld (1976). Stimulus-value patterns from that solution (aligned with stimulus dimensions described under "unidimensional judgments" above) were relatively unambiguous and parsimonious. The initial configuration entered for the schematic faces was determined by the location of the selected items on their two dimensions, described above (Lay et al., 1989). Analyses were undertaken treating the rating category boundaries in terms of interval (equal-appearing intervals) and ordinal (successive interval; see, e.g., Torgerson, 1958) properties. Results differed trivially; those based on the ordinal assumption are presented here.

The same stimulus values appear to be appropriate for the schizophrenic and control groups. Prior to computing a common solution for each stimulus set, separate solutions per set were undertaken for each group. Intercorrelations among groups of stimulus values for each dimension were substantial, ranging from an average of .82 for the affect descriptors to .99 for the schematic faces. It can be shown that if systematic usage among the controls exceeds that of the schizophrenia subgroups, correlations should be (significantly) higher when computed between schizophrenia subgroups and controls than when computed between schizophrenia subgroups themselves (e.g., Traub, 1994). Correlations between the schizophrenic subgroups in each instance were at least as high as those between these subgroups and controls. Therefore, the present dimensions, although initially identified among people without schizophrenia, were no less active in the judgments of the schizophrenia subgroups than they were among the controls.

Proportions of variance in judgments (scalar-product transformed) accounted for by the adopted common solutions were .43, .40, and .48 for personality descriptors, affect descriptors, and schematic faces, respectively. The first two values were similar to those obtained from earlier solutions (Neufeld, 1976). These values are not unlike ones found elsewhere in the literature with data sets of similar size (e.g., Houfek, 1992). Note that the aforementioned values are also the averaged sums of the salience weights squared. As would be expected if the model assumptions of common stimulus values and schizophrenia-specific processing deficits are correct, the observed proportions of variance accounted for in the combined sample for each of the three sets of stimuli were less than those for the control group but greater than those for the schizophrenic subgroups.

Stimulus values for the personality and affect descriptors conformed to those of previous studies (detailed in Carter & Neufeld, 1996); those for the schematic faces are presented in Figure 2. Labels of the verbal item dimensions were assigned according to the obtained patterns of stimulus projections and their alignment with those of the earlier analyses using these stimuli. Table 6 presents the means and standard deviations of the dimension-salience weights w_i for each group and set of items.[6] Prior to aggregating for each dimension across participants within groups, Kolmogorov-Smirnov tests for the tenability of a homogeneous normally distributed set of observations were applied. All tests were nonsignificant, with p values ranging from .382 to .998, and a mean of .651.[7]

---

[5] Alternatively, this finding is consistent with the competitor class of models involving global matching processes (e.g., Murdock, 1997).

[6] Consideration was given to the use of "flatted weights," whereby a three-dimensional solution, for example, may be "collapsed" onto a two-dimensional space. However, preference was given to the current solution format, for purposes of model testing and in deference to the earlier solution formats using the present stimuli.

[7] Pursuant to collapsing of data in the present instance, Chechile (1987) has forwarded certain observations with respect to the modified Weibull distribution (see Appendix A). Parameter estimates of δ and v based on mean trace-survival observations are interchangeable with the means of parameter values estimated from individual data protocols. Although Chechile's demonstration uses closed-form formulae for parameter estimates (unworkable here), it nevertheless applies in the present case, to the degree that the closed-form formulae are approached by LR-maximizing estimates (presented in Appendix C).

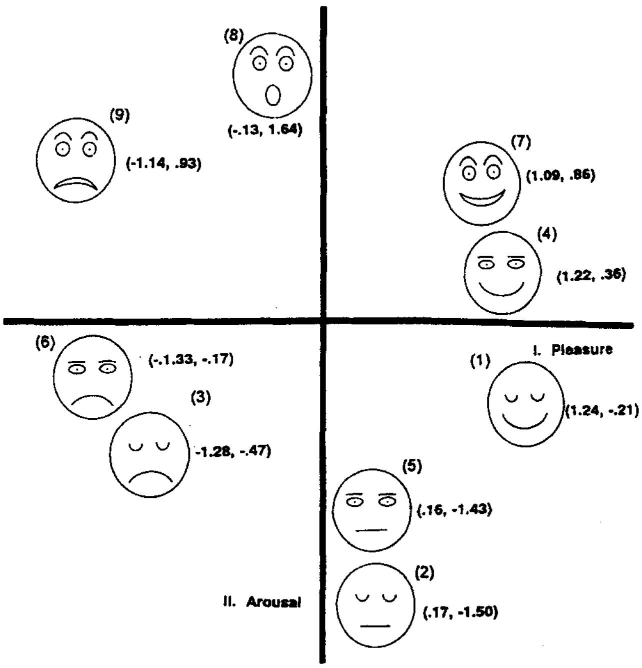

Figure 2. Projections of schematic faces on dimensions of pleasure and arousal.

In summary, the multidimensional scaling analysis provided the essential information regarding the content of multidimensional judgments in the form of dimension weights. Because the same stimulus values evidently are appropriate for all three groups, the critical differences in the content of judgments tenably are represented by the dimension weights. As predicted, the weights tend to be lower for the schizophrenia groups than for the control group, $F(2, 57) = 7.764, p < 0.01$.

Model Testing

The primary results from this section pertain to model fit-and-test procedures. Parameter values providing the closest fit between the model-predicted and observed MDS salience weights were estimated and implemented in model predictions. The candidate survivor functions implanted in the process model of salience weights included those of the Weibull, gamma, and exponential distributions, as well as their modified counterparts (all delineated in Appendix A). A brief explanation of relevant notation precedes selection of the most parsimonious model of close fit. The selected model is subjected to several complementary validity tests. Finally, one of the functions having notable precedent in memory-trace-survival research, and possessing certain merits with respect to the present data, is given additional scrutiny. Preliminary power calculations (Cohen, 1988, chap. 7; and related computations) indicated power for discriminating among the competing model versions was in the neighborhood of 0.80. Conditions for the validity of model testing were confirmed according to specifications laid out in several reviews on this topic (e.g., García Pérez, 1994).

Notation. In the following analyses, predicted dimension salience weights are denoted w_{xy}. This term refers to the mean INDSCAL-computed value of the second least salient dimension for stimulus set x, and diagnostic group y; $x, y = 1, 2, 3$. Therefore, where only two dimensions are involved (personality descriptors and schematic faces), w_{xy} represents the judgment-related salience of the intrinsically most salient dimension, and where three dimensions are involved (affect descriptors), w_{xy} represents the judgment-related salience of the intrinsically second most salient dimension, in each case for diagnostic group y.

The model representation of w_{xy} consists of $m_x\bar{F}(t')_{xy}$, where m_x is the intrinsic nondegraded salience of the second least salient dimension of stimulus set x, and $\bar{F}(t')_{xy}$ is the probability of survival of the memory trace of the encoded differences in stimulus values on that dimension. The variable t' in this expression indicates the train of cognitive-encoding subprocesses remaining for the least salient dimension, following completion of the second least salient dimension. As developed in Appendix B, t' is considered to be linearly related to the total encoding latency t of the least salient dimension. To economize on notation, mean observed unidimensional latencies, below, simply are denoted t (adjusted for estimated response-movement time of 160 ms).

Model-fit criterion and parameter estimation. Parameter estimation and tests of model fit were carried out by maximizing the likelihood ratio (Equation C4) and appropriating the associated χ^2,

Table 6
Mean Dimension Weights (and Interparticipant Standard Deviations in Parentheses) by Diagnosis for Each Stimulus Set

Dimension	Group: Paranoid schizophrenic	Nonparanoid schizophrenic	Control	% total judgment variance accounted for
Faces				
Pleasure	0.48 (0.21)	0.51 (0.21)	0.62 (0.21)	.48
Arousal	0.34 (0.12)	0.35 (0.14)	0.41 (0.12)	
Personality words				
Weak–strong	0.44 (0.11)	0.44 (0.20)	0.54 (0.12)	.43
Excitability	0.39 (0.09)	0.36 (0.16)	0.48 (0.08)	
Affective words				
Pleasant–unpleasant	0.38 (0.15)	0.38 (0.15)	0.51 (0.12)	.40
Level of activation	0.29 (0.10)	0.28 (0.10)	0.36 (0.07)	
Aggregation–activation	0.27 (0.08)	0.27 (0.09)	0.33 (0.06)	

as described in Appendix C. Model evaluation proceeded along two paths, each incorporating model nesting-nested relations (see, e.g., Bamber & van Santen, 1985). Fixing certain parameters of the Weibull distribution, or the gamma distribution, produces the exponential distribution (Appendix A). Exponential (or modified exponential) survivor functions, therefore, were tested against the modified Weibull or gamma models in which they were nested. In addition, within each of these model structures, nested models, with the m_x set equal to 1.0, were tested against their nesting counterparts, where the m_x were treated as free parameters. Tests of nested models indicate if the additional parameter estimation associated with the nesting model significantly improves model prediction.

Beginning with a fully constrained model, all parameters were set equal to 1.0. These parameters included δ, v, β, and m_x for the "modified Weibull distribution," and δ, v, k, and m_x for the "modified gamma distribution." Fixing the parameters in this way resulted in $\bar{F}(t)_{xy}$ of a "reduced exponential distribution." This model is nested in all other models, including the usual exponential distribution where v is allowed to vary. Every model with one or more free parameters produced a significantly superior fit to that based on the reduced exponential distribution.

Where β or k was released as a free parameter of the Weibull or gamma distribution, respectively, in only one instance was the model fit significantly improved. Specifically, in the case of the gamma distribution, allowing both δ and k to vary produced a superior fit relative to a model allowing only δ to vary, $\chi^2(8) = 22.38$, $p = 0.004$, versus $\chi^2(7) = 14.76$, $p = 0.040$, change in $\chi^2(1) = 7.62$, $p = 0.006$. In this instance, k took on a value of 3, and δ was 0.63. The test on goodness of fit, however, remained significant (i.e., variance of observed data residual to that predicted by the model exceeded what could tenably be ascribed to sampling error). In other instances, where β or k was free to vary, best fits inevitably converged on its floor value of 1.0. Focus, consequently, falls on results obtained for the exponential and modified exponential distributions.

Significant improvement in fit occurred when v was allowed to vary, in addition to δ, $\chi^2(8) = 22.38$, $p = 0.004$, versus $\chi^2(7) = 12.11$, $p = 0.10$, change in $\chi^2(1) = 10.27$, $p = 0.001$. Also, the introduction of the m_x as free parameters improved model fit over that where δ alone was allowed to vary, $\chi^2(8) = 22.38$, $p = 0.004$, versus $\chi^2(5) = 3.45$, $p = 0.631$, change in $\chi^2(3) = 18.93$, $p = 0.003$. Similar changes attended the addition of m_x to v, even though the test on model fit with v alone as a free parameter was not significant, $\chi^2(8) = 12.11$, $p = 0.15$, versus $\chi^2(5) = 0.95$,[8] $p = 0.97$, change in $\chi^2(3) = 11.17$, $p = 0.01$. The addition of δ as a free parameter in this model left the computed χ^2 essentially unaltered.

The improvement in fit accompanying the inclusion of m_x as free parameters was examined in light of Akaike's (1974) Information Criterion (AIC; see Appendix C). The obtained values clearly favored the model including m_x as free parameters, AIC = 8.9462 versus 14.1145, the lower value indicating model superiority (see, e.g., Bozdogan, in press).

On balance, results supported the exponential distribution, accompanied by m_x as free parameters, as the best-fitting model. Parameter estimates were as follows: 0.12 for v, 0.97 for m_1, 1.05 for m_2, and 0.68 for m_3, where subscripts 1, 2, and 3 refer to the second least salient dimension of the schematic faces, personality descriptors, and the affect descriptors, respectively. These parameter values appeared reasonable; for example, the value for m_3 of 0.68 is plausible, considering that this intrinsic salience is identified with the second most salient rather than the most salient dimension of similarity among the affect descriptors.[9]

Figure 3 presents the probability of trace survival for the second least salient dimension of each of the three stimulus sets and each group, estimated as w_{xy}/m_x, plotted against the corresponding estimated latency for encoding a stimulus set's least salient dimension, t. Also appearing as the solid line in the figure is the survivor function of the best-fitting model, described above, specifically $\exp(-0.12t)$, from which the respective model-predicted probabilities of trace survival, $\bar{F}(t)_{xy}$, were obtained.[10]

In summary, the best-fitting function according to the maximum likelihood criteria was the exponential. Additional parameters associated with the modified Weibull and modified gamma functions failed to improve the fit. Parameters related to intrinsic saliences did tend to improve the fit and, as predicted, were defensibly the same across groups.

Additional validity tests. The validity of the exponential-distribution survivor function for the current data was evaluated using supplementary methods. First, the strength of association between the model-predicted and observed values of the dimensional salience weights was compared with that prescribed by a simple linear relation between the relevant unidimensional encoding latencies and salience weights. Second, cross-validations of model predictions across participant subsamples were undertaken (see, e.g., Browne, in press). Third, generalization tests were included, whereby the model was tested against an alternate response parameter (Busmeyer & Wang, in press); in the present instance, encoding latencies as well as dimensional salience weights were subjected to prediction. Fourth, the assignment of model parameters to experimental factors was interchanged from the initial model-specified assignment; in particular, intrinsic dimensional salience m_x was required to vary across participant groups rather than stimulus sets. Fifth, correspondence of results from observations aggregated across participants to those from desegregated data was examined. Finally, certain qualitative predictions comprising more pronounced group separation on more intrinsically salient similarity dimensions were considered.

The proposed model accounted for more of the variance in response content than was accounted for by the response latencies alone. The value of r^2 was computed between the observed values of w_{xy} and the model-predicted values, $\exp(-0.12t_{xy})m_{xy}$ (Cobb,

[8] The value of χ^2 of 0.95 associated with the best-fitting model was considerably less than the expected value of χ^2, or 5.0 (i.e., the mean of the χ^2 distribution, with 5 degrees of freedom). However, the density function ("height of the curve") of the χ^2 distribution $f(\chi^2_{[df=5]})$ corresponding to the obtained χ^2 was reasonable, being 0.077, that of the expected value being 0.122, and the maximum value, corresponding to the mode, being 0.154.

[9] Auxilliary analyses were carried out, applying the fit-and-test procedures to the verbal stimuli only. Findings essentially duplicated those using all stimulus sets simultaneously.

[10] Evaluation of goodness of fit was undertaken using an alternative to the above χ^2 tests. This alternative, detailed in Neufeld and McCarty (1994), is based on an analysis of variance format. Results from these tests were in accordance with those of the χ^2 tests, including obtained improvement in fit upon casting m_x as free parameters and nonsignificant differences between the best-fitting model and the observed data.

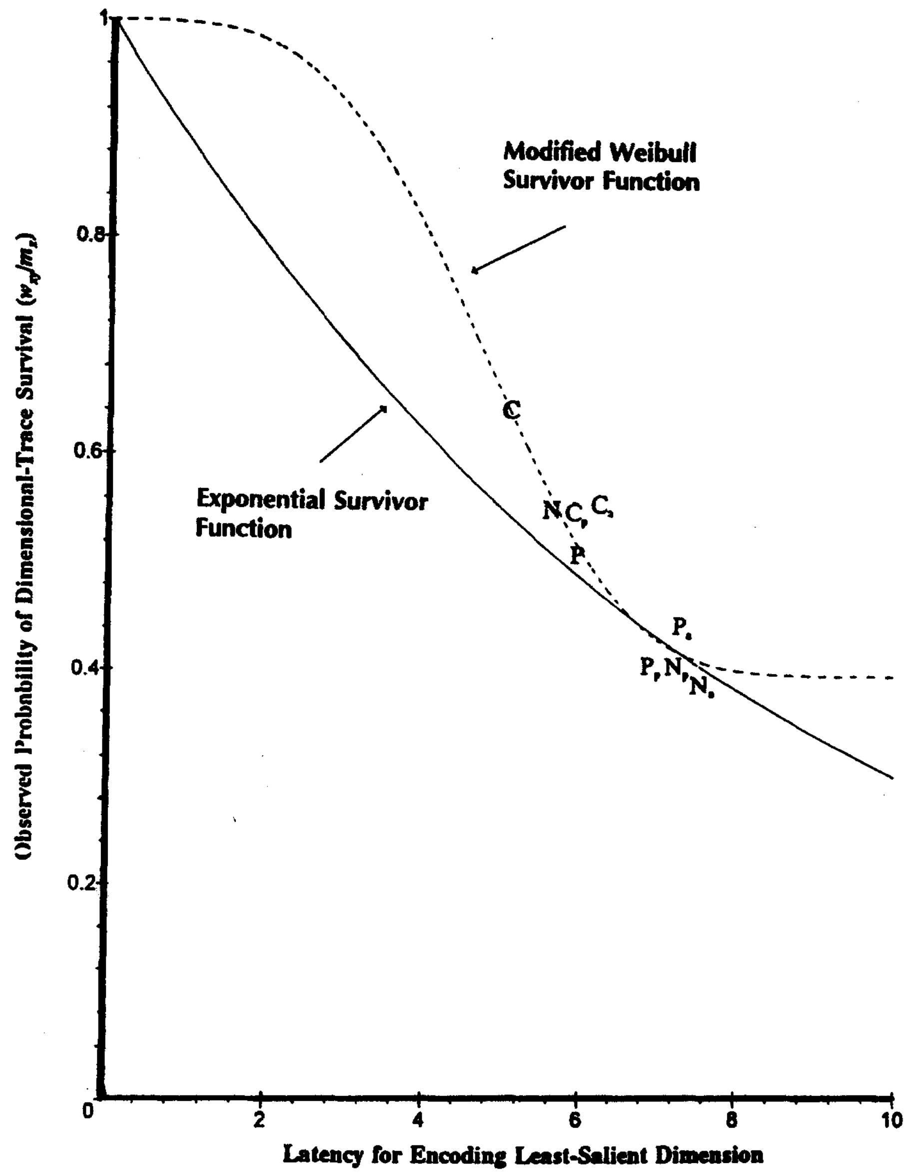

Figure 3. Observed probability of trace survival for the second least salient dimension for each stimulus set and group, and model-generated survivor functions, $\exp(-0.12t)$, solid line, and $1 - 0.606 + 0.606 \exp(-(0.194t)^{3.607})$, dotted line, plotted against unidimensional judgment latencies, t. Groups are denoted by uppercase letters: paranoid (P), nonparanoid (N) schizophrenic patients, and controls (C). Lowercase subscripts indicate personality descriptors (p), affect descriptors (a), and faces (no subscript).

1981). The obtained value was 0.925. In contrast, that obtained between w_{xy} and the raw latencies was 0.682.

For purposes of cross-validation, each sample of 20 participants was randomly divided into two subsamples of 10 each. This division was repeated three times, allowing for three rounds of cross-validation. In each case, parameter values were estimated separately for each subsample. Correspondence between predicted and observed values, quantified as r^2, was calculated using the model predictions from one subsample and observed values from the other. Each subsample of each pair provided both predictions and observations, making for a total of six cross-validation estimates.

It was noted prior to cross-validation that the best-fitting model allowed predictions of unidimensional encoding latencies, as well as dimension salience weights. The model predicts that the unidimensional encoding latency for the second least-salient dimension of stimulus set x among group y, t_{xy}, will be $[\ln(m_x) - \ln(w_{xy})]/v$. Thus, both w_{xy} and t_{xy} were subjected to prediction, making for generalization testing in addition to cross-validation. For purposes of contrast, r^2 was computed between the raw values of t_{xy} of one subsample and w_{xy} of its counterpart.

The mean value of r^2, where w_{xy} values were predicted, was 0.36, while that where t_{xy} was predicted was 0.40. This reduction from the r^2 for the intact sample appears attributable in part to attrition of data stability accompanying diminished sample size. To illustrate, the mean r^2 where w_{xy} was predicted using parameter estimates within the same subsample was 0.45. Finally, the mean value of r^2 between w_{xy} and raw values of t_{xy} was 0.07.

In the models discussed above, the intrinsic dimensional saliences, m_x, were held constant among groups but were allowed to vary across stimulus sets. This pattern of variation assumes that intrinsic salience is equal across groups. An alternate possibility comprised variation in m_x across groups but constancy across stimulus sets. These conditions were introduced and the competing model was subjected to estimation-and-test procedures. An acceptable fit was not attainable, apart from bizarre parameter values, such as v and m_x both tending to infinity.

The generality of findings from the aggregated data was examined with respect to the individual participant level of analysis. The resulting release of measurement error—essentially, a Gaussian-noise source not incorporated into the present model construction (cf. Smith, 1995)—prevented acceptable goodness-of-fit values. On the other hand, findings resembled those of the aggregated data in other important ways. Specifically, sources of elevation in fit were similar. For example, releasing the m_x as free parameters, in addition to v, led to statistically significant improvements. Although the extreme of disaggregation—a trial-by-trial analysis of judgments—would be ideal, it would require substantial development of the current model to accommodate the resulting noise (see, e.g., Carter, Neufeld, & Benn, 1998).

In the formulation presented here, unidimensional encoding of schizophrenia patients is characterized by a larger number of subprocesses relative to that of controls. It may be conjectured, therefore, that the intrinsic salience of a similarity dimension m_{xy} would stand to be eroded to a greater degree where it tends to be followed by the encoding of two other dimensions, rather than only one. Presumably, a pair of subsequently encoded dimensions potentially embody more retroactive interference than does a singleton. The effects of increased interference, in turn, should include a more pronounced reduction in w_{xy} of a dimension followed by encoding of two rather than one other dimension.

The affect descriptors rendered a dimensional triad, thus affording such a test. Separation on w_{xy} should be more evident for the intrinsically most salient dimension than for the intrinsically second most salient dimension; the former is considered to be followed by completion of dimensions second and third in the order of intrinsic salience, whereas the latter generally is considered to be followed by completion of the least salient dimension. From an analysis of variance perspective, a test of the groups (three levels) by dimensions (two levels—most vs. second most salient) interaction on the w_{xy} values should be significant. Accordingly, along with significant main effects, the result for the interaction was significant, $F(2, 57) = 3.17, p < 0.05$, reflecting an attenuated loss of salience among the schizophrenia participants of the second versus first dimension.

In line with this result, the second-order ratio comprising $[w_{1c}/w_{2c}]/[w_{1s}/w_{2s}]$ should exceed 1.0, as follows. In this formula, w_{xy} denotes the mean salience weight for the first or second most intrinsically salient dimension for control or schizophrenia participants, $x = 1, 2$; $y = c, s$. According to the preceding reasoning, the survival probability of Dimension 1 relative to Dimension 2 for the schizophrenia participants should be less than that for the controls. The second-order ratio highlights such differences in comparative degredation because, by the model, it is equal to $\{[m_1\bar{F}(t)_{1c}]/[m_2\bar{F}(t)_{2c}]\}/\{[m_1\bar{F}(t)_{1s}]/[m_2\bar{F}(t)_{2s}]\} = \{\bar{F}(t)_{1c}/\bar{F}(t)_{2c}\}/\{\bar{F}(t)_{1s}/\bar{F}(t)_{2s}\} = \{\bar{F}(t)_{1c}/\bar{F}(t)_{1s}\}/\{\bar{F}(t)_{2c}/\bar{F}(t)_{2s}\}$. This value exceeded 1.0 in each instance, being 1.04 in the case of controls and nonparanoid schizophrenia participants and 1.08 in the case of controls and paranoid schizophrenia participants.

Further evaluation of the Weibull function. As an additional check on model variation, closer examination was given to viability of the modified Weibull structure because of its demonstrated validity in memory-trace research proper (Chechile, 1987). Certain aspects of the present model-fitting criteria may have circumvented favorable features of this structure. Pursuant to this possibility, hypothetical survivor functions of the modified Weibull distribution (see Figure A1 in Appendix A) visually were superimposed onto the plot displayed in Figure 3. These distribution trajectories more closely approximated the displayed points than did those of the selected exponential model. They performed better especially for values of w_{xy}/m_x of the face stimuli, such as that computed for the controls (denoted C in Figure 3). The value of N_x for the face stimuli was less than its value for the verbal descriptors, potentially moderating adverse effects on model fit of judgments surrounding the former stimuli. This possibility is especially apparent in the Pearsonian format of χ^2, Equation C5 of Appendix C, whose results essentially duplicate those of the likelihood-ratio format used above (see Appendix C).

It was decided, therefore, to fit $\bar{F}(t)$ of the modified Weibull distribution to the values of w_{xy}/m_x using the method of least squares. Thus, the sum of squared deviations of model predictions from observed values was minimized. This alternate "cost function" bypassed variation in N_x. For calculations to proceed, it was necessary to import the existing values of m_x (enumerated above). Allowing the m_x to be free parameters, instead, produced artificially low sums of squares, with unreasonably high parameter estimates. Free parameters, therefore, were restricted to v, β, and k, only. Also, whereas β in the above analyses was an integer, as was k of the gamma distribution, in the present analysis it was allowed to vary continuously, thereby potentially improving model fit (cf. Chechile, 1987).

Comparisons to the selected exponential model gave mixed results. The best-fitting modified Weibull model was one where v was equal to 0.194, δ was 0.606, and β was 3.607. Confirming visual impression, its sum of squared deviations was approximately one fourth that of the exponential contender. This function is displayed as the dotted line in Figure 3. Using predictions obtained from the function, χ^2 was recomputed and found to be 0.50.[11] The associated p value exceeded .90, whether 6 or 3 degrees of freedom were used.

The value of r^2 for this model was 0.946, as compared with 0.925 for the selected exponential model. Viewing m_x as free parameters for both models, AIC was 8.94 for the selected exponential model and 12.5 for the modified Weibull model. Excluding the m_x as free parameters, the value for the modified Weibull becomes 9.5.

[11] Regarding density-function values for χ^2, $f(\chi^2_{(df=3)})$ corresponding to 0.50 was remarkably similar to the maximum (modal) value of $f(\chi^2_{(df=3)})$, the amounts being 0.220 and 0.242, respectively. The value of $f(\chi^2_{(df=3)})$ for the observed χ^2 exceeded that of the expected $\chi^2_{(df=3)}$ of 3.0, which was 0.1542.

Overall, the modified Weibull distribution provided a plausible model for the present observations. Its merits included approximation of certain values of w_{xy}/m_x that had departed from predictions of the selected exponential model. On the other hand, based on comparative values of χ^2, r^2, and AIC, the selected exponential model evidently was more parsimonious.

Discussion

Results of this investigation support a model integrating substance of multidimensional stimulus judgments with speed of unidimensional encoding. Substance, in this case, pertains to the consistency with which multidimensional judgments are governed by systematic stimulus properties. A lengthened process of dimensional encoding taking place later in the judgment trial appears to elevate the risk of losing dimensional information acquired earlier in the trial. Increased stages of encoding among schizophrenic individuals are deemed to compromise the influence on judgments of earlier encoded dimensions. The formal account incorporates models of multidimensional judgments, stimulus encoding, and memory-trace dynamics, and implements documented findings of performance deviations in schizophrenia.

Candidate Trace-Survivor Functions

The trace-survivor function supported by standard tests of fit was that of the exponential distribution. This function is simpler than one shown to express trace-survival dynamics in bona fide memory research (Chechile, 1987). According to the exponential distribution, an enduring memory trace's vulnerability to imminent failure remains constant while subsequent cognitive events unfold (Appendix A).

The function appropriated from memory-research findings (Chechile, 1987) was that of the modified Weibull distribution. The trajectory of this distribution's survivor function conformed to predicted values in certain unique respects. Its proximity to data points exceeded that of the function described above, according to the sum-of-squared-deviations criterion. Thus, the dynamics of trace survival pertaining to memory-paradigm items (e.g., consonant trigrams) may also characterize those of encoded dimensional properties.

At present, both the above survivor functions appear viable, on different grounds. Such status of alternate models is not out of the ordinary in formal model testing; it illustrates an advantage of formal methods—that of highlighting existing boundaries on certainty and the possible need for future diagnostics (cf. McFall, Treat, & Viken, 1997). In any case, although the specifics of the two survivor functions technically render them mutually exclusive, plausibility of the broader model relating judgment content to encoding speed does not strictly depend on the presence of one or the other. Note that the purpose of the present work was not so much to differentiate among particular survivor functions as to establish the viability of the overall integrative model amidst one or more trace-survival characterizations.

Returning to the functions themselves, the modified Weibull distribution prescribes an initial increase followed by a gradual decrease in the susceptibility to impending failure of a persevering trace, and the survivor function asymptotes at some value greater than zero. This function would suggest that no rehearsal occurs to maintain the trace but that some traces are invulnerable to failure. In contrast, the exponential function prescribes a constant risk of failure and the survivor function asymptotes at zero. It would imply some form of rehearsal to maintain the memory trace, but nevertheless all traces fail with sufficient passage of time. Finally, the results of this investigation did not affirm the gamma survivor function, which would have suggested not only the presence of rehearsal but also that any given trace might be retrieved in spite of partial failure of its "storage subprocesses" (Appendix A).

Model-Parameter Assignment and Estimation

We now consider the broader model transcending specific survivor functions. Certain parameter values were allotted to all three participant groups in common. One such value was that of the intrinsic dimension salience, m_x. In contrast to constraining the same value of m_x to groups and allowing this parameter to vary across stimulus sets, the opposite combination of constancy across sets and variation over groups led to untenable results.

Comparability of dimension salience m_x evidently was matched by comparability of dimension-encoding rates u_x. Release of u_x to vary across groups did not increase model fit to the unidimensional-judgment data. As well, constraining the same values of u_x to groups in the modeling of multidimensional judgments did not unseat adequacy of model fit to response latencies. The designation of equal encoding rates amidst increased encoding subprocesses is compatible with previous extensive analyses addressed to these parameters (Neufeld & Williamson, 1996).

Turning attention to the parameter reflecting rate of trace loss, v, assignment of differential values across groups again was not required for acceptable model fit. The amount of encoding stages remaining for an uncompleted dimension was considered to be larger for the schizophrenic participants than controls. The resulting increased risk of trace loss, however, apparently was not abetted by greater susceptibility to interference. Similar findings of trace integrity have been obtained from other formal models of schizophrenia memory (Bamber, 1979; see below). On the face of it, this observation seems at variance with certain previous findings on comparative susceptibility to interference and forgetting (Broga & Neufeld, 1981b). Significantly poorer retrieval was observed among paranoid schizophrenic subgroups on the Peterson–Peterson (1959) consonant trigram paradigm. On closer examination, however, those findings appear to mesh with the present observations, as follows.

In the Peterson–Peterson paradigm, a series of consonant trigrams were studied for a limited time period (2 s each), with retrieval tests following an intervening distracter task—counting backward by 3s. Extended encoding stages should detract from the amount of rehearsal available to individual trigrams under time constraints. Diminished rehearsal iterations, in turn, should compromise the integrity of resulting item traces. Similar inferences have been drawn from reduced performance on spatial-memory tasks, where to-be-remembered item locations have been presented for fixed time periods (Neufeld, Mather, Merskey, & Russell, 1995).

Of particular relevance to the aforementioned possibilities is the study by Bamber (1979), in which memory-trace states among schizophrenic patients and controls were formally modeled, aided by conventional memory tasks. Bamber's modeling indicated that trace properties per se were intact among the schizophrenic patients, but that initial input was impaired. The latter function involved reading and representation of common words whose presentation was limited to 4 s apiece. As noted above, a prolonged encoding process would stand to diminish the effectiveness with which presented items were implemented. Performance on other short-term memory tasks has indicated adverse effects of prolonged encoding on initial item preparation, again when temporal restrictions attended the encoding process (discussed in Highgate & Neufeld, 1986).

Model Structure

Consistent with the perspective that psychopathology is the result of a dysfunction in normal mental processes (Masten & Braswell, 1991), the present investigation found that the same model could account for judgment latency and content among schizophrenic and control groups. In particular, important aspects of the model, such as the intrinsic salience of constituent dimensions as well as encoding and trace-loss rates, tenably were common to all groups.

The model structures applied to the predicted data were constant across the diagnostic groups. In the case of multidimensional encoding, for example, there was no evidence that serial processing of constituent dimensions predominated among the schizophrenic participants, while parallel processing to a greater extent characterized controls. A constancy of processing structures is in keeping with previous findings where informal and quasiformal models of performance have been used to study schizophrenia information processing (Neufeld & Broga, 1981). It is accordant, as well, with findings using formal mathematical models designed expressly to detect the differential presence of parallel versus serial processing (Vollick & Neufeld, 1999).

Model structures depicting the progression of trace loss (stochastic-distribution survivor functions) also parsimoniously were common across diagnostic status. Bamber (1979) modeled trace states across retention periods, using other formal methods. He too found that similar structures sufficed to express trace maintenance among his schizophrenic and control samples.

Furthermore, for the functions retained here, their conformity to empirical observations was substantial. The values of r^2 were solidly in the range of those reported from settings investigating formal models of normal cognitive psychology; conversely, the values of r^2 for the competing linear relation between latency and dimension-salience values were less than those obtained for competing models in those settings (e.g., Smith, 1995).

The restriction of acceptable fit specifically to the present theoretically grounded survivor functions bears on the possibility that results are attributable simply to "generalized deficit" among the schizophrenia participants. If relations between encoding-latency and response-content data were merely an expression of generalized deficit, a linear relation of w_{xy} to t_{xy} might well have sufficed. This is not to say that it is impossible for generalized deficit to have been the agent of the obtained results. However, its expression precisely as the present quantitatively exquisite functions (or even some approximation thereof) would have been fortuitous at best (see Knight & Silverstein, 1999). These observations thus underscore an additional advantage of formal models: They afford what amounts to Popperian bold conjectures (see, e.g., Meehl, 1978). At the same time, their boldness is founded on solid axiomatic derivations (see McFall & Townsend, 1998).

The present model structures can be examined for possibilities of disconfirmation regarding relations between encoding latency and judgment content. Potentially useful models in principal should permit such options. Specifically, the current formulations indicate zones where latency differences are not met with differences in judgment content. Such zones are those where the survivor functions reach asymptote. They include, in the present cases, values of t beyond 45 for the exponential distribution and values beyond 8.0 for the modified Weibull distribution (depicted in Figure 3).

Qualifications

Emphasis in the present analysis has been placed on effects of retroactive interference with continuation of extant encoding traces by residual encoding activity. In line with this emphasis, conventional analysis indicated that group separation on multidimensional-scaling salience values w_{xy} was attenuated with diminished intrinsic dimensional salience. Also, in the modeling of multidimensional encoding, releasing constraints to allow the less intrinsically salient dimension to be completed first did not significantly improve model fit. On the other hand, group differences in w_{xy} on the least salient dimensions were not notably absent (see Table 6). Regarding this observation, note that dimensions encoded earlier in the sequence of completions may impinge on the products of subsequent completions (proactive interference), especially during response-deployment phases (Gardiner, Craik, & Birtwhistle, 1972). Proliferation of encoding stages should accentuate adverse effects of prior encoding operations on the judgmental influence of later completions. Further, proliferation of encoding stages potentially makes for greater "noise in the processing system," detracting from the systematic use of encoding traces, including those tending to be last in the order of production (Neufeld & Broga, 1981). Such possibilities do not discredit the present emphasis on retroactive interference; they do, nevertheless, point out that the model as formulated does not incorporate such possible effects.[12] An extended model may provide for such additional influences and implicate more observations; comprehensiveness would be attained, nevertheless, amidst increased complexity.

The presented model was developed with reference to a delimited set of observations involving multidimensional similarity judgments and stimulus-encoding times among designated diagnostic groups. Reference to existing cognitive-process models helps to outline additional inferential boundaries of the current formulation (e.g., Ashby, 1992). Certain accounts have addressed probabilities of "same–different" stimulus judgments and judgment reaction time as a function of interstimulus multidimensional distance (Takane & Sergent, 1983). Nosofsky (e.g., 1991), focusing on stimulus categorization, provided for effects of attention-eliciting properties of constituent stimulus dimensions and changes in such properties over categorization trials. Individuals may mod-

[12] Such influences potentially undermine the protuberance of schizophrenia's putatively enhanced retroactive interference with earlier encoded dimensions. Nevertheless, a more pronounced schizophrenia-related degradation surrounding these dimensions prevailed overall. Of the 10 pertinent second-order ratios (described above) computable from data presented in Table 5, 8 exceeded the critical value of 1.0, ranging from 1.02 to 1.10, there being one "tie," *binomial* $p \approx .022$, $\chi^2_{(1)} = 4.9$, $p < .027$.

ify their allocation of attentional resources as trials progress (Nosofsky, 1992). In the present formulation, intrinsic salience m_x was deemed to be constant across similarity-judgment trials. This simplification appeared acceptable for the present modeling purposes. However, its adequacy in the current case does not contraindicate the presence of dynamic features, whereby the present m_x would be a summary index of fluctuating attention-eliciting properties. Other variables, such as values of t and response movement time, also undoubtedly waver in ways not specified by the present formulation, but their less complex treatments suffice for the current purposes of parsimony.

Additional considerations surround the viability of constraints imposed by the present multidimensional scaling algorithm designating a common stimulus-dimensional space for all participants. It is possible, for example, that schizophrenic participants attended to additional dimensions. Nevertheless, the designated dimensions and their salience properties were duly present in the semantic networks of the schizophrenia participants. This presence was evidenced in the configurations of stimulus projections from the individual-groups solutions as well the untenability of a model structure depicting unequal intrinsic salience across groups. Although sharing a dimensional subspace, nonetheless, schizophrenia participants may have attended to idiosyncratic dimensions. A detailed assessment of findings from multidimensional scaling analyses and analyses of mnemonic organization is compatible with this possibility (Neufeld, 1984). Observe, however, that the influence of extraneous dimensions runs counter to the obtained conformity of observations to model predictions. In other words, the present model fits the obtained data well enough to override such possible detraction.

Other aspects of potential group inequalities not directly assessed in the present analysis comprise response decision-and-execution processes. These processes were evaluated in the model-fit-and-test procedures applied to the encoding latencies. However, the time required for these particular mechanisms defensibly was regarded as being common to the groups (see Tables 3, 4, and 5). This assumption was based on convergent evidence from several experimental paradigms implicating response processes (enumerated in Neufeld et al., 1993).

Future Directions

The present investigation has demonstrated that schizophrenic deficits in response content on a complex task—in this case, overall similarity judgments—may be accounted for by delays in response latency on a simpler task—in this case, unidimensional judgments. The gamma survivor function (which implies rehearsal and retrieval after partial trace failure) was not supported as a candidate to describe this relationship. Further investigation, however, is necessary to distinguish between the exponential survivor function (which implies rehearsal and ultimate failure of all traces) and the modified Weibull (which implies no rehearsal, but allows for invulnerable traces). As in previous research (Neufeld et al., 1993), increased latency was attributed to increased number of encoding subprocesses among people suffering from schizophrenia. A parallel structure seemed to describe this encoding process best, but factorial technology (e.g., Townsend & Nozawa, 1995) could be deployed in future investigations of model structure. Accurate encoding of individual dimensions enhanced performance on this task, but further study of tasks where such traces may detract from performance (e.g., judgments of less salient dimensions) would be appropriate.

Possible neuroanatomical correlates of reduced encoding efficiency come to the fore, as follows. It has been suggested that this deficit is identified with frontal-lobe regions, essentially because of the putative role of stimulus encoding in certain tests of frontal integrity, involving multidimensional stimuli (Neufeld & Williamson, 1996). Included are the Wisconsin Card Sorting and related tests. Such suggestions are highly inferential and indirect. A more substantial strategy would consist of monitoring brain activation during cognitive performance and using activation measures having the temporal and spatial resolution necessary to track formally estimated cognitive events. The availability of high-field-strength (4.0-Tesla) functional magnetic resonance imaging, and approval of its use with human participants, increases the viability of this option (currently under way in this setting).

Meanwhile, compatible with neuropsychological measures implicating frontal regions (discussed above) are those of magnetic resonance spectroscopy. Studies using such analyses have indicated decreased glutamatergic activity in the medial prefrontal region among never-treated schizophrenic patients (Bartha et al., 1997), as well as abnormality in prefrontal-region membrane metabolism among more chronic patients (Potwarka et al., 1999).

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control, 19,* 716–723.

Ashby, F. G. (1982). Deriving extract predictions from the cascade model. *Psychological Review, 89,* 599–607.

Ashby, F. G. (1992). *Multidimensional models of perception and cognition.* Hillsdale, NJ: Erlbaum.

Ashby, F. G., Maddox, W. T., & Lee, W. W. (1994). On the dangers of averaging across participants when using multidimensional scaling or the similarity-choice model. *Psychological Science, 5,* 144–151.

Baggaley, A. (1964). *Intermediate correlational methods.* New York: Wiley.

Bamber, D. (1979). State-trace analysis: A method of testing simple theories of causation. *Journal of Mathematical Psychology, 19,* 137–181.

Bamber, D., & van Santen, J. P. (1985). How many parameters can a model have and still be testable? *Journal of Mathematical Psychology, 29,* 443–473.

Bartha, R., Williamson, P. C., Drost, D. J., Malla, A., Carr, T. J., Cortese, L., Canaran, G., Rylett, R. J., & Neufeld, R. W. J. (1997). Measurement of glutamate and glutamine in the medial prefrontal cortex of never-treated schizophrenic patients and healthy controls by proton magnetic resonance spectroscopy. *Archives of General Psychiatry, 54,* 959–965.

Blishen, B. R., Carroll, W. K., & Moore, C. (1987). The 1981 socioeconomic index for occupations in Canada. *Canadian Review of Sociology and Anthropology, 24,* 465–488.

Bozdogan, H. (in press). Akaike's information criterion and recent developments in informational complexity. *Journal of Mathematical Psychology.*

Broga, M. I., & Neufeld, R. W. J. (1981a). Evaluation of information-sequential aspects of schizophrenic performance: I. Framework and current findings. *Journal of Nervous and Mental Disease, 169,* 559–568.

Broga, M. I., & Neufeld, R. W. J. (1981b). Multivariate cognitive performance levels and response styles among paranoid and nonparanoid schizophrenics. *Journal of Abnormal Psychology, 90,* 495–509.

Browne, M. W. (in press). Cross-validation methods. *Journal of Mathematical Psychology.*

Bush, L. (1973). Individual-differences multidimensional scaling of adjectives denoting affect. *Journal of Personality and Social Psychology, 25,* 50–57.

Busmeyer, J. R., & Wang, Y. (in press). Model comparisons and model selections based on generalization test methodology. *Journal of Mathematical Psychology.*

Carroll, J. D., & Arabie, P. (1980). Multidimensional scaling. In M. R. Rozenzweig & L. W. Porter (Eds.), *Annual Review of Psychology* (Vol. 31, pp. 607–649). Palo Alto, CA: Annual Reviews.

Carroll, J. D., & Chang, J. J. (1970). Analysis of individual differences in multidimensional scaling via an N-way generalization of "Eckart-Young" decomposition. *Psychometrika, 35,* 283–319.

Carter, J. R., & Neufeld, R. W. J. (1996). *A process model of salience deficits in multidimensional judgments* (Research Bulletin No. 738). London, Ontario, Canada: University of Western Ontario.

Carter, J. R., Neufeld, R. W. J., & Benn, K. D. (1998). Application of process models in assessment psychology: Potential assets and challenges. *Psychological Assessment, 10,* 379–395.

Cegalis, J. A., Leen, D., & Solomon, E. J. (1977). Attention in schizophrenia: An analysis of selectivity in the functional visual field. *Journal of Abnormal Psychology, 86,* 470–482.

Chandler, J. P. (1975). *STEPIT 7.4* [Computer program]. Stillwater, OK: Oklahoma State University, Computer Science Department.

Chechile, R. A. (1987). Trace susceptibility theory. *Journal of Experimental Psychology: General, 116,* 203–222.

Cobb, L. (1981). Stochastic differential equations for the social sciences. In L. Cobb & R. M. Thrall (Eds.), *Mathematical frontiers of the social and policy sciences* (pp. 37–68). Boulder, CO: Westview Press & American Association for the Advancement of Science.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences.* Hillsdale, NJ: Erlbaum.

Cromwell, R. L., & Snyder, C. R. (Eds.). (1993). *Schizophrenia: Origins, processes, treatment, and outcome.* New York: Oxford University Press.

Davis, J. K. (1976). Comparative doses and costs of antipsychotic medication. *Archives of General Psychiatry, 33,* 858–861.

Dobson, D., & Neufeld, R. W. J. (1982). Paranoid–nonparanoid schizophrenic distinctions in the implementation of external conceptual constraints. *Journal of Nervous and Mental Disease, 170,* 614–621.

Doob, J. L. (1953). *Stochastic processes.* New York: Wiley.

Foulds, G. A., Caine, T. M., Adams, A., & Owen, A. (1965). *Personality and personal illness.* London: Tavistock.

Galambos, J. (1978). *The asymptotic theory of extreme order statistics.* New York: Wiley.

García Pérez, M. A. (1994). Parameter estimation and goodness-of-fit testing in multinomial models. *British Journal of Mathematical and Statistical Psychology, 47,* 247–282.

Gardiner, J. M., Craik, F. I. M., & Birtwhistle, J. (1972). Retrieval cues and release from proactive inhibition. *Journal of Experimental Psychology, 103,* 71–78.

Grünwald, P. (in press). Model selection based on minimum description length. *Journal of Mathematical Psychology.*

Highgate, S., & Neufeld, R. W. J. (1986). Schizophrenic memory-search performance involving nonverbal stimulus properties. *Journal of Abnormal Psychology, 95,* 67–73.

Hoffman, R. E., Rapaport, J., Ameli, R., McGlashan, T. H., Harcherik, D., & Servan-Schreiber, D. (1995). A neural network simulation of hallucinated "voices" and associated speech perception impairments in schizophrenic patients. *Journal of Cognitive Neuroscience, 7,* 479–496.

Hoffman, R. E., Stopek, S., & Andreason, N. S. (1986). A comparative study of manic versus schizophrenic speech disorganization. *Archives of General Psychiatry, 43,* 831–838.

Hollingshead, B. A. (1957). *Two Factor Index of Social Position.* Unpublished manuscript. (Available from Jeffrey R. Carter, Department of Psychology, University of Western Ontario, London, Ontario, Canada N6A 5C2)

Houfek, J. F. (1992). Nurses' perceptions of the dimensions of nursing care episodes. *Nursing Research, 41,* 280–285.

Hughes, R. C., Reuter-Lorenz, P. A., Nozawa, G., & Fendrich, R. (1994). Visual-auditory interactions in sensory-motor processing: Saccades versus manual responses. *Journal of Experimental Psychology: Human Perception and Performance, 20,* 131–153.

Knight, R. A., & Silverstein, S. M. (1999). *A process-oriented approach for averting confounds resulting from general performance deficiencies in schizophrenia.* Manuscript submitted for publication.

Koh, S. D., Kayton, L., & Berry, R. (1973). Mnemonic organization in young nonpsychotic schizophrenics. *Journal of Abnormal Psychology, 81,* 299–310.

Krogh, C. M. (Ed.). (1992). *Compendium of pharmaceuticals and specialties.* Toronto: Canadian Pharmaceutical Association.

Larzelere, R. E., & Mulaik, S. A. (1977). Single-sample tests for many correlations. *Psychological Bulletin, 84,* 557–569.

Lay, K. L., Waters, E., & Park, K. A. (1989). Maternal responsiveness and child compliance: The role of mood as a mediator. *Child Development, 60,* 1405–1411.

Lubow, R. E., Weiner, I., Schlossberg, A., & Baruch, I. (1987). Latent inhibition and schizophrenia. *Bulletin of the Psychonomic Society, 25,* 464–467.

Magaro, P., Abrams, L., & Cantrell, P. (1981). The Maine Scale of Paranoid and Nonparanoid Schizophrenia: Reliability and validity. *Journal of Consulting and Clinical Psychology, 49,* 438–447.

Masten, A. S., & Braswell, L. (1991). Developmental psychopathology: An integrative framework. In P. R. Martin et al. (Eds.), *Handbook of behavior therapy and psychological science: An integrative approach* (pp. 35–56). Pergamon General Psychology Series (Vol. 164). New York: Pergamon Press.

McFall, R. M., & Townsend, J. T. (1998). Foundations of psychological assessment: Implications for cognitive assessment in clinical science. *Psychological Assessment, 10,* 316–330.

McFall, R. M., Treat, T. A., & Viken, R. J. (1997). Contributors of cognitive theory to new behavioral treatments. *Psychological Science, 8,* 174–176.

Meehl, P. E. (1978). Theoretical risks and tabular asterisks: Sir Karl, Sir Ronald, and the slow progress of soft psychology. *Journal of Consulting and Clinical Psychology, 46,* 806–843.

Meyers, J. L., & Well, A. D. (1993). *Research design and statistical analysis.* New York: HarperCollins.

Murdock, B. B. (1997). Context and mediators in a theory of distributed associative memory (TODAM2). *Psychological Review, 104,* 839–862.

Neufeld, R. W. J. (1975). Multidimensional scaling of schizophrenics' and normals' perceptions of verbal similarity. *Journal of Abnormal Psychology, 84,* 498–507.

Neufeld, R. W. J. (1976). Simultaneous processing of multiple stimulus dimensions among paranoid and nonparanoid schizophrenics. *Multivariate Behavioral Research, 4,* 425–442.

Neufeld, R. W. J. (1984). Are semantic networks of schizophrenic samples intact? *Behavioural and Brain Sciences, 7,* 749–750.

Neufeld, R. W. J. (Ed.). (1998). Introduction to special section on process models in psychological assessment. *Psychological Assessment, 10,* 307–315.

Neufeld, R. W. J. (1999a). Dynamic differentials of stress and coping. *Psychological Review, 106,* 385–397.

Neufeld, R. W. J. (1999b). Stochastic models of information processing under stress. Manuscript submitted for publication.

Neufeld, R. W. J., & Broga, M. I. (1981). Evaluation of information sequential aspects of schizophrenic performance: II. Research strategies and methodological issues. *Journal of Nervous and Mental Disease, 169,* 569–579.

Neufeld, R. W. J., & Gardner, R. C. (1990). Data aggregation in evaluating psychological constructs: Multivariate and logical deductive considerations. *Journal of Mathematical Psychology, 24,* 276–296.

Neufeld, R. W. J., Mather, J. A., Merskey, H., & Russell, N. C. (1995). Multivariate structure of eye movement dysfunction in schizophrenia. *Multivariate Experimental Clinical Research, 11,* 1–21.

Neufeld, R. W. J., & McCarty, T. (1994). A formal analysis of stressor and stress-proneness effects on basic information processing. *British Journal of Mathematical and Statistical Psychology, 47,* 193–226.

Neufeld, R. W. J., Vollick, D., & Highgate, S. (1993). Stochastic modelling of stimulus encoding and memory search in paranoid schizophrenia: Clinical and theoretical implications. In R. L. Cromwell & R. Snyder (Eds.), *Schizophrenia: Origins, processes, treatment, and outcome: The Second Kansas Series in Clinical Psychology,* (pp. 176–198). New York: Oxford University Press.

Neufeld, R. W. J., & Williamson, P. (1996). Neuropsychological correlates of positive symptoms: Delusions and hallucinations. In C. Pantelis, H. E. Nelson, & T. R. E. Barnes (Eds.), *Schizophrenia: A neuropsychological perspective* (pp. 205–235). London: Wiley.

Nosofsky, R. M. (1991). Tests of an exemplar model for relating perceptual classification and recognition memory. *Journal of Experimental Psychology: Human Perception and Performance, 17,* 3–27.

Nosofsky, R. M. (1992). Similarity scaling and cognitive process models. *Annual Review of Psychology, 43,* 25–33.

Oldfield, R. C. (1971). The assessment and analysis of handedness: The Edinburgh inventory. *Neuropsychology, 9,* 97–113.

Paitich, D., & Crawford, G. (1970). *A multiple-choice version of the WAIS vocabulary.* Unpublished manuscript, Clarke Institute of Psychiatry, Toronto, Ontario, Canada. (Available from Jeffrey R. Carter, Department of Psychology, University of Western Ontario, London, Ontario, Canada N6A 5C2)

Paulman, R. G., Devous, M. D., Gregory, R. R., Herman, J. H., Jennings, L., Bonte, F. J., Nasrallah, H. A., & Raese, J. D. (1990). Hypofrontality and cognitive impairment in schizophrenia: Dynamic single-photon tomography and neuropsychological assessment of schizophrenic brain function. *Biological Psychiatry, 27,* 377–399.

Peterson, L. R., & Peterson, M. J. (1959). Short-term retention of individual verbal items. *Journal of Experimental Psychology, 58,* 193–198.

Piotrowski, S. M. (1983). *Orthogonal dichotic manipulations of stimulus contrast and discriminability: Implications for serial and parallel processing models.* Unpublished master's thesis, Purdue University, West Lafayette, IN.

Pishkin, V., & Bourne, L. E. (1981). Abstraction and the use of available information by schizophrenic and normal participants. *Journal of Abnormal Psychology, 90,* 197–203.

Potwarka, J. J., Drost, D. J., Williamson, P. C., Carr, T., Canaran, G., Rylett, W. J., & Neufeld, R. W. J. (1999). An ^{1}H decoupled ^{31}P chemical shift imaging study of medicated schizophrenic patients and healthy controls. *Biological Psychiatry, 45,* 687–693.

Schiffman, S. S., Reynolds, M. L., & Young, F. W. (1981). *Introduction to multidimensional scaling: Theory, methods, and applications.* New York: Academic Press.

Smith, P. L. (1994). Fechner's legacy and challenge [Review of *The wave theory of difference and similarity*]. *Journal of Mathematical Psychology, 38,* 407–420.

Smith, P. L. (1995). Psychophysically principled models of visual simple reaction time. *Psychological Review, 102,* 567–593.

Snodgrass, J. G., & Townsend, J. T. (1980). Comparing parallel and serial models: Theory and implementation. *Journal of Experimental Psychology: Human Perception and Performance, 6,* 330–354.

Spence, I., & Domoney, D. W. (1974). Single participant incomplete designs for nonmetric multidimensional scaling. *Psychometrika, 39,* 469–490.

Spitzer, R. L., Endicott, J., & Robins, E. (1978). Research Diagnostic Criteria: Rationale and reliability. *Archives of General Psychiatry, 35,* 773–782.

Strauss, M. (1973). Behavioral differences between acute and chronic schizophrenics: Course of psychosis, effects of institutionalization or sampling bias? *Psychological Bulletin, 79,* 271–279.

Takane, Y., & Sergent, J. (1983). Multidimensional scaling models for reaction times and same–different judgments. *Psychometrika, 48,* 393–423.

Torgerson, W. S. (1958). *Theory and methods of scaling.* New York: Wiley.

Torgerson, W. S. (1965). Multidimensional scaling of similarity. *Psychometrika, 30,* 379–393.

Townsend, J. T. (1984). Uncovering mental processes with factorial experiments. *Journal of Mathematical Psychology, 28,* 363–400.

Townsend, J. T. (1992). On the proper scales for reaction time. In H. Geissler, S. W. Link, & J. T. Townsend (Eds.), *Cognition, information processing, and psychophysics: Basic issues* (pp. 105–120). Hillsdale, NJ: Erlbaum.

Townsend, J. T., & Ashby, F. G. (1983). *Stochastic modelling of elementary psychological processes.* Cambridge, England: Cambridge University Press.

Townsend, J. T., & Nozawa, G. (1995). Spatio-temporal properties of elementary perception: An investigation of parallel, serial, and coactive theories. *Journal of Mathematical Psychology, 39,* 321–359.

Traub, R. E. (1994). *Reliability for the social sciences: Theory and applications.* Thousand Oaks, CA: Sage.

Tucker, L. R. (1972). Relationships between multidimensional scaling and three-mode factor analysis. *Psychometrika, 37,* 3–27.

Tversky, A. (1977). Features of similarity. *Psychological Review, 84,* 327–352.

Vollick, D., & Neufeld, R. W. J. (1999). *Stochastic modelling of means and variances of stimulus encoding times in paranoid and nonparanoid schizophrenic patients.* Manuscript in preparation.

Wyatt, R. J., & Torgow, J. S. (1976). A comparison of equivalent clinical potencies of neuroleptics as used to treat schizophrenia and affective disorders. *Journal of Psychiatric Research, 13,* 91–98.

Young, F. W., Takane, Y. L., & Lewyckyi, R. J. (1988). ALSCAL [Computer software]. Chicago: SPSS Inc.

Appendix A

Candidate Stochastic Trace Survivor Functions

The probabilistic dynamics of trace failure may be characterized by survivor functions of certain stochastic distributions. Included here are the modified Weibull distribution (Chechile, 1987) and the gamma and exponential distributions (see, e.g., Neufeld, 1998). The modified Weibull distribution effectively has been shown to portray the dynamic properties of the survival of stored memory traces, at least for items comprising consonant trigrams (Chechile, 1987). Gamma and exponential distributions can somewhat resemble the modified Weibull distribution in the contours of their respective survivor functions (see below).

In the following descriptions, reference is made to the density function, distribution function, and the above-mentioned survivor function of the respective distributions. Briefly, the density function is proportional to the relative frequency of a process ending at time t (e.g., relative frequency of trace loss). The distribution function corresponds to the probability of process finalization at or before t, $0 \le t$, and the survivor function indicates the probability of process noncompletion by time t. Another distribution property, the hazard function, is described below, following presentation of its components, the density function and survivor function.

Modified Weibull Distribution

The Weibull distribution has as its density function, $f(t)$,

$$\beta v(vt)^{\beta-1}\exp(-(vt)^{\beta}),$$

where v is the rate of trace failure, $0 < v$; β is the shape factor, $0 < \beta$, affecting the mode of the Weibull distribution and indicating the rate of increase in its hazard function; and t denotes time.

The survivor function of the Weibull distribution, $\bar{F}(t)$, is

$$1 - \int_0^t f(t)dt = \exp\,[-(vt)^{\beta}].$$

A modification to the Weibull distribution entails provision for the possibility of invulnerable status of a stored trace. The probability of trace failure at $t = \infty$ is potentially less than 1.0. Thus, the modified density function becomes $\delta f(t)$, δ indicating the probability of trace failure at $t = \infty$; $0 < \delta \le 1.0$. Accordingly,

$$\int_0^\infty \delta f(t)dt = \delta.$$

In the instance of the Weibull distribution,

$$\delta f(t) = \delta\beta v(vt)^{\beta-1}\exp[-(vt)^{\beta}],$$

and the survivor function, $\bar{F}(t)$, or $1 - \delta F(t)$, becomes

$$1 - \delta\{1 - \exp[-(vt)^{\beta}]\} = 1 - \delta + \delta\exp(-(vt)^{\beta}) \text{ (see Figure A1)}.$$

Where $\beta = 1$, the Weibull and modified Weibull distributions reduce to the exponential and modified exponential distributions, below.

Gamma

The density function for the gamma distribution is

$$\frac{(vt)^{k-1}}{(k-1)!}\,v\exp\,(-vt);\; k = 1, 2, \ldots,$$

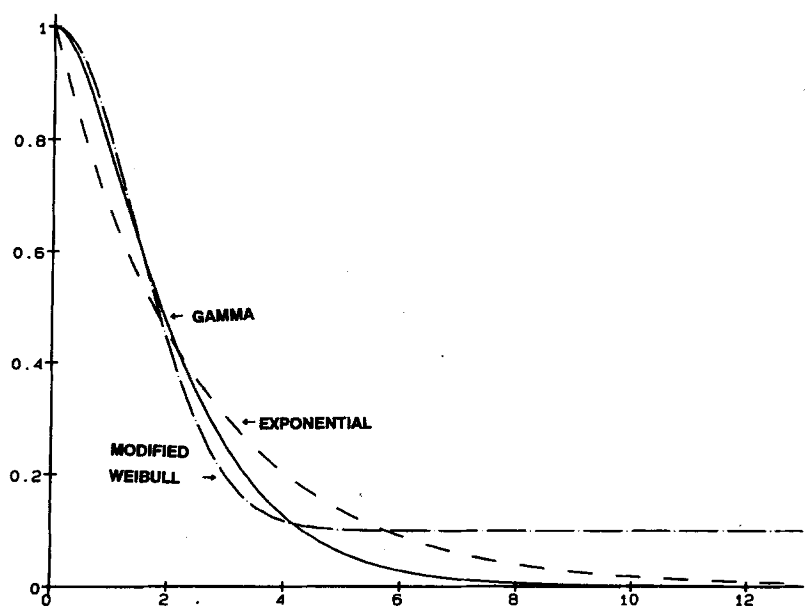

Figure A1. Survivor functions of the modified Weibull, gamma, and exponential distributions: for modified Weibull, $\beta = 2$, $v = 0.5$, $\delta = 0.9$; for gamma, $k = 2$, $v = 0.9$; and for exponential, $v = 0.4$. Note that the modified gamma and exponential distributions resemble their unmodified counterparts, except they assymptote at $1 - \delta$ rather than 0, where $\delta < 1.0$.

the distribution function, $F(t)$ is

$$1 - \sum_{j=0}^{k-1} \frac{(vt)^j}{j!} \exp(-vt),$$

and the survivor function is

$$\sum_{j=0}^{k-1} \frac{(vt)^j}{j!} \exp(-vt).$$

The modified distribution function is

$$\delta\left[1 - \sum_{j=0}^{k-1} \frac{(vt)^j}{j!} \exp(-vt)\right],$$

and the modified survivor function becomes

$$1 - \delta + \delta \sum_{j=0}^{k-1} \frac{(vt)^j}{j!} \exp(-vt).$$

Where $k = 1$, the gamma and modified gamma distribution reduce the exponential and modified exponential distributions.

Exponential

As implied above, the exponential distribution's density function is $v \exp(-vt)$ and its distribution function is

$$\int_o^t f(t)dt = 1 - \exp(-vt).$$

The survivor function, therefore, is e^{-vt}, and the modified survivor function is

$$1 - \delta + \delta e^{-vt}.$$

The gamma and exponential survivor functions can approximate the trajectory of stochastic trace survival specified by the modified Weibull distribution (see Figure A1). Thus, these additional distributions can be tendered as possible characterizations of dynamic trace-survival properties. Although the trajectories of the above survivor functions can be similar, given appropriate parameter values, they nevertheless signify model differences carrying theoretical import. The exponential distribution implies rehearsal, or continuing upkeep of the memorial trace (cf. Chechile, 1987). The trace is cast as being under siege, and eventually succumbs, but there is no increase of momentary vulnerability of the trace with continuing onslaught. Mathematically, this feature is indicated by a constant hazard function, $H(t) = f(t)/\bar{F}(t)$—that is, the conditional rate of trace failure at time t, given survival at least up to t; specifically, the value of $H(t) = v \exp(-vt)/[\exp(-vt)] = v$. In the case of the Weibull distribution, the hazard function is

$$H(t) = v\beta(vt)^{\beta-1},$$

which monotonically increases if β exceeds 1.0 and decreases if β is less than 1.0. Progressive vulnerability attends increase in $H(t)$, and the opposite.

The gamma distribution depicts a process made up of k stages, or subprocesses. The latency for each subprocess (intercompletion time) is exponential, with rate v; a trace can be retrieved if even one of the k "storage subprocesses" remains, analogous to a spider's web staying suspended by one thread (cf. Chechile, 1987). As each intercompletion time is exponentially distributed, each one's hazard function, taken separately, once more is constant. Hence, each hypothetical storage subprocess maintains its same level of momentary vulnerability while it continues.

Note that the hazard functions of the modified Weibull and modified gamma distributions are nonmonotonic, where $\delta < 1.0$, and β, or k, >1.0; they increase at the outset, plateau, and then gradually decrease. As with an increasing hazard function, the shape of a nonmonotonic hazard function is considered to indicate nonrehearsal, or an absence of memorial-trace replenishment (Chechile, 1987). A rough analogy entails the purchase of a new automobile. Production and other defects appear fairly soon after purchase and the initial stress of sustained driving. Following such trauma, performance gradually stabilizes.

Appendix B

Residual Subprocesses of an Uncompleted Dimension

In the case of serial processing of dimensions, encoding is considered to take place sequentially; commencement of one dimension proceeds following completion of another. For the parallel case, processing is considered to commence on each dimension simultaneously but not to be completed simultaneously. Instead, completions are distributed stochastically over time. In the serial case, the full complement of subprocesses for a remaining dimension(s) simply transpire after the earlier dimension is finished. More salient dimensions are deemed on average to be undertaken before less salient ones, likelihoods of commencement thereby varying accordingly (see, e.g., Townsend & Ashby, 1983, chap. 11).

For purposes of presenting the parallel case, the two encoding processes, a and b, are considered to comprise the same number of subprocesses. It is stated without proof that the equality is a simplifying, but not required, condition for the inferences that follow.

The latency of an individual encoding process is represented by a gamma distribution (see Appendix A). In the case of encoding, parameter k represents encoding stages or subprocesses, and parameter u is aligned with encoding rate (speed of transacting the respective subprocesses; Neufeld et al., 1993). Given two such processes proceeding in parallel (simultaneous gamma process), the probability of completing process a first, $Pr(a, b)$, is available from a variation on the Pascal distribution (described in Carter, Neufeld, & Benn, 1998), as follows. Adapting equations from Appendix A of Townsend (1984),

$$Pr(a, b) = \sum_{s=0}^{k-1} \binom{k+s-1}{s} \left(\frac{u_a}{u_a + u_b}\right)^k \left(\frac{u_b}{u_a + u_b}\right)^s, \quad \text{(B1)}$$

and

$$Pr(b, a) = \sum_{s=0}^{k-1} \binom{k+s-1}{s} \left(\frac{u_b}{u_a + u_b}\right)^k \left(\frac{u_a}{u_a + u_b}\right)^s,$$

where $Pr(a, b)$ is the probability of completing process a first, $Pr(b, a)$ is the probability of completing process b first, u_a is the encoding-rate parameter for process a, and u_b is the encoding-rate parameter for process b. Note that "Poisson rate parameters" are deemed to be an increasing function of stimulus or stimulus-feature intensity (see, e.g., Smith, 1994). As process a is identified with the more salient dimension, therefore, u_a is considered to exceed u_b. Hence, process a is more likely to be completed first. The conditional expectations of residual subprocesses, given a first, and given b first, are available as

$$E(k_{res}|a, b) = \frac{\left[\sum_{s=0}^{k-1} \binom{k+s-1}{s} \left(\frac{u_a}{u_a+u_b}\right)^k \left(\frac{u_b}{u_a+u_b}\right)^s (k-s)\right]}{Pr(a, b)}, \quad \text{(B2)}$$

and

$$E(k_{res}|b, a) = \frac{\left[\sum_{s=0}^{k-1} \binom{k+s-1}{s} \left(\frac{u_b}{u_a+u_b}\right)^k \left(\frac{u_a}{u_a+u_b}\right)^s (k-s)\right]}{Pr(b, a)}.$$

As the structure of these equations is complex, computer computations are necessary to examine variation in the above quantities with changes in k, and inequalities in u_a and u_b. They reveal that the probability of completing process a first approaches 1.0 fairly quickly, as u_a increases over u_b.

Computer computations also show that residual subprocesses increase essentially linearly with k, more so as u_a exceeds u_b. Overall, allowing u_a to exceed u_b leads to a high probability of process a being completed first and a positive, essentially linear, association between k and k_{res}. These observations are detailed in Carter and Neufeld (1996; available from either author).

The basically linear relation between k and k_{res} affords an estimate of the latter amount according to the encoding duration of the associated dimension. Note that under a gamma-distributed encoding latency, the mean encoding time $E(T)$ is k/u, whereby $k = uE(T)$. Considering their linear relation, $k_{res} = ck$, where c is a constant of proportionality. Thus $k_{res} = cuE(T)$, where cu now is the constant of proportionality with respect to time. Although the survivor functions of the present modeling are constructed with reference to time (see Appendix A), they could be constructed with reference to k_{res}; v would simply change to reflect the replacement of t with k_{res}. As well, the ratio-scale properties of latency are preserved with conversion to k_{res}. That is, the units of measurement are related by a constant, and the origin of 0 has the same meaning for both scales (see Townsend, 1992).

Appendix C

χ^2 and Related Formulae Serving in Parameter Estimation and Model Testing

Pseudo-χ^2 ($\hat{\chi}^2$)

Estimation of parameters of tendered models routinely entails the maximization of correspondence between observed data and model predictions. Conversely, discrepancy between data and predictions, summarized as a "cost function," is to be minimized. The following cost function is useful in the present case where data comprise distribution moments, notably means and variances (Townsend, 1984):

$$\sum_{q=1}^{g} \frac{(\bar{x}_{pred,q} - \bar{x}_{obs,q})^2}{\bar{x}_{pred,q}} + \sum_{q=1}^{g} \frac{(SD_{pred,q} - SD_{obs,q})^2}{SD_{pred,q}}, \quad \text{(C1)}$$

where $\bar{x}_{pred,q}$ = model-predicted value for the qth mean, $SD_{pred,q}$ = model-predicted value for the qth standard deviation, $\bar{x}_{obs,q}$ and $SD_{obs,q}$ are the corresponding observed values, and g is the number of means and standard deviations involved in the analysis. This cost function is especially useful for parameter estimation using function-minimizing procedures such as those described in the text (or equivalently maximization of the inverse of Equation C1). The function is labeled pseudo-χ^2 as it has a χ^2 format; however, values are affected by units of measurement and are not necessarily distributed expressly as χ^2 (Townsend & Ashby, 1983, p. 432).

Analysis of Variance χ^2

The following version of χ^2 resembles that frequently found in formal treatments of the analysis of variance:

$$\chi^2 = \sum_{q=1}^{g} \frac{(\bar{x}_{obs,q} - \bar{x}_{pred,q})^2}{Var_q/N_q}. \quad \text{(C2)}$$

In this equation, $\bar{x}_{pred,q}$ = the model prediction of the qth mean, $\bar{x}_{obs,q}$ is the corresponding observed value, Var_q/N_q is the variance associated with the qth mean, N_q is the number of judgments making up the qth mean (36 in the case of schematic faces and 66 in the case of words), and g is the number of sets of judgments for which means are available. Degrees of freedom are: g − (number of theoretical − model's parameter estimates).

Likelihood Ratio χ^2

The statistic $G^2 = -2\log_e(LR)$ is asymptotically distributed as χ^2 with increasing N, the total number of observations in the formulae below. The numerator of the likelihood ratio (LR) consists of the likelihood of the observed data, given the theoretical model with fewer parameters than the number of independent observational categories; the denominator consists of the likelihood of the observed data, given a "model" with as many parameters as independent observational categories (see below). Degrees of freedom are equal to the difference between the number of parameters in the theoretical model and the number of independent observational categories.

The binomial likelihood of n events of a given category occurring over the course of N trials is

$$\binom{N}{n} p^n (1-p)^{N-n},$$

where p is the probability of the category of event occurring on any trial. If p is prescribed by the theoretical model, it is denoted θ, and where it is a probability based on the observed data, it is denoted P. The binomial LR then takes the form

$$\frac{\binom{N}{n} \theta^n (1-\theta)^{N-n}}{\binom{N}{n} P^n (1-P)^{N-n}}. \quad \text{(C3)}$$

In the present application, $\theta = \bar{F}(t)$, the survivor function prescribed by the theoretical distribution under consideration. The value of P is determined by the observed probability of the event category, specifically n/N, which also is the maximum-likelihood estimate of p, given the data at hand.

Using the proposed model, we show that the number of judgments affected by dimension x in group y, n_{xy}, is available as a function of the observed salience value w_{xy}, specifically $N_x w_{xy}/m_x$. Here, N_x is the number of judgments in stimulus set x. To elaborate, observe that w_{xy} is defined as $\bar{F}(t)m_x$; therefore, the number of judgments affected by the dimension is the probability of the latter's trace survival multiplied against the number of judgments involved. Consequently, the joint binomial LR of the observed values taken across all stimulus sets and groups is

$$\prod_x^3 \prod_y^3 \frac{\binom{N_x}{N_x w_{xy}/m_x} (\bar{F}(t)_{xy})^{N_x w_{xy}/m_x} (1-\bar{F}(t)_{xy})^{N_x(1-w_{xy}/m_x)}}{\binom{N_x}{N_x w_{xy}/m_x} (w_{xy}/m_x)^{N_x w_{xy}/m_x} (1-w_{xy}/m_x)^{N_x(1-w_{xy}/m_x)}}. \quad (C4)$$

As the number of independent observational categories in the present application is 9, degrees of freedom are equal to 9, less the number of parameters specified by the theoretical model.

Pearsonian χ^2

With terms analogous to those of Equation C3, above, this general format of χ^2 is

$$\sum N\left[\frac{(P-\theta)^2}{\theta} + \frac{((1-P)-(1-\theta))^2}{(1-\theta)}\right].$$

Using the present terms and design results in

$$\sum_x^3 \sum_y^3 N_x\left[\frac{(w_{xy}/m_x - \bar{F}(t)_{xy})^2}{\bar{F}(t)_{xy}} + \frac{((1-w_{xy}/m_x)-(1-\bar{F}(t)_{xy}))^2}{1-\bar{F}(t)_{xy}}\right]. \quad (C5)$$

Note that in practice this version of χ^2, and G^2, above, yield similar results; they are equivalent for large N.

Akaike's Information Criterion (AIC)

This index of model performance takes into account the number of free parameters involved in generating an obtained χ^2. In this way, efficiency of the model structure is considered. The index is

$$G^2 + 2(\text{number of parameters estimated}), \quad (C6)$$

where lower values of the index are preferable.

Received May 12, 1997
Revision received February 16, 1999
Accepted March 16, 1999 ■