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QUANTITATIVE RESPONSE TIME TECHNOLOGY FOR MEASURING COGNITIVE-PROCESSING CAPACITY IN CLINICAL STUDIES

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The dichotomy of automatic versus controlled processing has been of great importance in cognitive psychology (Hasher & Zacks, 1979; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977; Treisman & Gormican, 1988). These concepts have often been defined more or less operationally rather than strictly in terms of theoretical constructs. Performance maintaining its efficiency as opposed to deteriorating as workload increases has been the norm. For instance, Schneider and Shiffrin (1977), in a massive study of these phenomena in the context of visual search, saw automatic processing as being associated with flat or almost-flat response time functions as the

visual display set size increased. Increasing response time functions indicated ordinary controlled, or *effortful*, processing.

Nonetheless, theoretically oriented processing concepts have been associated, sometimes relatively loosely, sometimes quite tightly, with the dichotomy at least since the publication of Schneider and Shiffrin's (1977) seminal work, which suggested multifaceted change in information processing over the course of repetition. From this viewpoint, automatic processing entails the processing of task elements in parallel (or synchronously) rather than in serial (or successively) and does not tax processing capacity, whereby an increase in task load does not incur deterioration in performance efficiency (speed and/or accuracy).

Controlled processing, furthermore, has been thought to be *self-terminating*, meaning that search can cease as soon as sufficient information for a correct response is acquired. Nonetheless, the incorporation of unnecessary elements can be allowed in the case of automatic processing, at least for selected paradigms (Schneider & Shiffrin, 1977; see also Kahneman & Chajczyk, 1983; Shiffrin, 1988). Processing of all items in a trial is referred to as *exhaustive processing*; thus, it can be seen that automatic processing demands the satisfaction of several criteria on processing dimensions (see, e.g., Townsend, 1974; Townsend & Ashby, 1983).

To be sure, domains of clinical investigation invoking all or part of this multidimensional construct have included cognition in schizophrenia (C. S. Carter, Robertson, Chaderjian, Celaya, & Nordahl, 1992; Gold, Wilk, McMahon, Buchanan, & Luck, 2003; Granholm, Asarnow, & Marder, 1996a, 1996b; Magaro, 1983; Narr, Green, Capetillo-Cunliffe, Toga, & Zaidel, 2003; Nuechterlein & Dawson, 1984), affective disorders (Hartlage, Alloy, Vázquez, & Dykman, 1993; MacLeod & Rutherford, 1998; Sheppard & Teasdale, 2000), addictions (Baxter & Hinson, 2001), and anxiety disorders (Brewin, 1989; Brewin, Dalgleish, & Joseph, 1996; Brewin & Holmes, 2003; Teachman & Woody, 2003), among others. Even the search for possible leads for improvements in psychotherapy has not been exempt (Kirsh & Lynn, 1999).

As stated previously, the primary constituents of the automatic and controlled–effortful characterization of cognitive performance entail architecture of the processing system, notably whether task elements are transacted in parallel or serial fashion, capacity, and termination criteria. These components nevertheless are intrinsically bound up with one another in the ways they affect performance, and as will be apparent in the following discourse, measurement of any one must take account of the others (Townsend & Ashby, 1983; Townsend & Wenger, 2004a).[1] Despite being

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[1] Analyses addressing conflation of these constituents occurring to their informal treatment in clinical science were presented by Neufeld (1996).

closely interlaced, these components are separable in empirically tractable ways but not without a methodology rigorously grounded in quantitative theorizing.

In this chapter, we spotlight what arguably is the most prominent member of the above trio from the standpoint of clinical science and assessment-processing capacity. Applications in the clinical arena of methods for deciphering architecture have been taken up in a separate venue (Townsend, Fific, & Neufeld, in press).

Over the course of presentation, mathematically entrenched measures and their empirical estimates will be described: the capacity index, $H(t)$; the Capacity Ratio (CR); and the Capacity OR Coefficient, $C_o(t)$. $H(t)$ is a general measure of cognitive work done over a given time interval. It is launched from an axiomatic definition of the capacity concept and is linked to work and energy in physics. CR compares values of $H(t)$ between two conditions of processing, or between groups under study. It is very versatile and is useful for bringing to bear the assets of $H(t)$ on the ubiquitous assessment of capacity of clinical compared with control groups. $C_o(t)$ is used to characterize a processing system of interest with reference to a benchmark system—one whose efficiency in processing a given cognitive load is unchanged with an increase in load. The studied system's response to increased cognitive load is classified as expressing *limited capacity*, whereby efficiency decreases with increased load; *unlimited capacity*, whereby, like the benchmark system, efficiency remains unchanged; or *super capacity*, whereby efficiency actually increases with increased load. $C_o(t)$ can be especially useful in assessing the system of interest as it operates under normal circumstances and then to evaluate whether and how it is perturbed with psychopathology. Each of the above quantities is developed with respect to specific clinical data.

Specific definitions and estimation of $H(t)$ and CR now lead off. They are developed and then illustratively applied to a study of cognitive functioning of anxiety-prone individuals. The remaining index, $C_o(t)$, similarly is developed and then illustrated, this time with respect to memory search in schizophrenia. Along the way, we examine challenges of implementation in clinical science and avenues to potential resolution.

QUANTIFYING PROCESSING CAPACITY

A measure of cognitive-processing capacity is presented here. It is prescribed by formal theoretical developments addressed to task performance response times. The measure has the desirable features of being robust, in terms of transcending individual and task differences in latency distributions, and empirically tractable, in terms of being readily computable from obtained

data. As part and parcel of derivations emanating from fundamental mathematical concepts (axioms and rigorous definitions and assumptions), such measures qualify as being mandated specifically by theory, resembling measurement practices of longer established sciences (Meehl, 1978; cf. McFall & Townsend, 1998). An added bonus turns out to be the construct validity with which formal theoretical measures are endowed, owing to the substantive properties derived from their analytical infrastructure (Braithwaite, 1968; cf. the "construct representation" of Embretson, 1983).[2]

We begin by describing summary depictions of probability distributions (i.e., frequency functions) of events—in this case, cognitive process completions. That is, some type of cognitive task is performed, typically on a set of entities that can be perceptual or more cognitive, as in memory search. These distributions represent the quantitative building blocks of the present capacity index, $H(t)$. They also capture the essence of latency in its roles as dependent variable and performance index in studies of cognition generally. In this treatment, performance inaccuracy is deemed to be inconsequential, that is, relatively low, and not aligned with latency in ways that compromise inferences drawn from the latter (see, e.g., Townsend & Wenger, 2004a). Note that the distributions being characterized are both stochastic and dynamical, features of theory again earmarking longer established sciences (e.g., Penrose, 2004).

DISTRIBUTION PROPERTIES AND THEIR ROLES IN DEFINING THE CAPACITY INDEX: $H(t)$

Consider the completion of a cognitive task or task segment (process). The task, for example, may be one of memory search. The participant must detect the presence of a visually presented alphanumeric item (*probe item*) among a set of memorized items (*memory set*). Of course, the probe itself must somehow be transformed and prepared for the comparison process (*probe-item encoding*). Unless the interval between memory set presentation and presentation of the probe is very short, placement of the memory set in short-term memory should not influence the response times. The critical cognitive events, particularly the search through memory, obviously are not completed at the same point in time on every trial. Instead, completion times vary, and their relative frequencies produce a corresponding probability distribution. In the case of a continuous distribution, as a function of continuous time t, the frequency function is known as a *probability density function*,

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[2] Such *ab initio* analytical construct validity contrasts that where the claimed substantive significance of a model parameter is supported from ensuing mathematical explorations of its properties (Neufeld, in press).
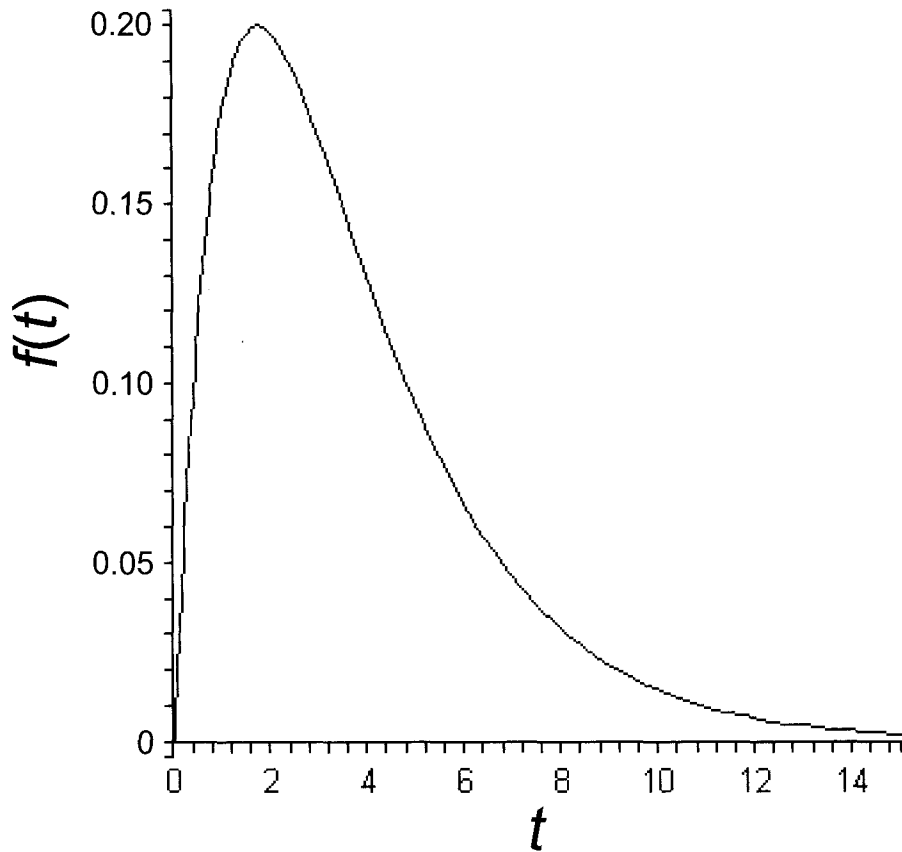
Figure 7.1. Density function *f(t)* for a theoretical distribution of processing latencies.

or simply *density function*, $f(t)$ (not to be confused with the ordinary concept of density in the field of physics). Hence, $f(t)$ is proportional to completion frequency (see Figure 7.1). The density function of time t is analogous to the height of the familiar normal distribution as a function of z.

The probability of event occurrence at or before a specific value of t (i.e., completion of processing before time t) comprises the cumulative probability distribution function $F(t)$. Replacing t with t' in $f(t)$, $F(t)$ is the integral (if time were discrete instead of continuous, it would be a sum) of $f(t')$ from 0 to t. The survivor function $S(t)$ is the complement of $F(t)$, or the probability of event occurrence after t, and is therefore just $S(t) = 1 - F(t)$. Accordingly, $S(t)$ is the integral of $f(t')$ from t to infinity. Finally, the hazard function, $h(t)$, expresses the instantaneous rate of event completion, given that it has not yet occurred, or $f(t)/S(t)$. That is, given that the event has not occurred by time t, $h(t)$ gives the likelihood that it will occur in the next instant. Its curious name derives from its use in actuarial science
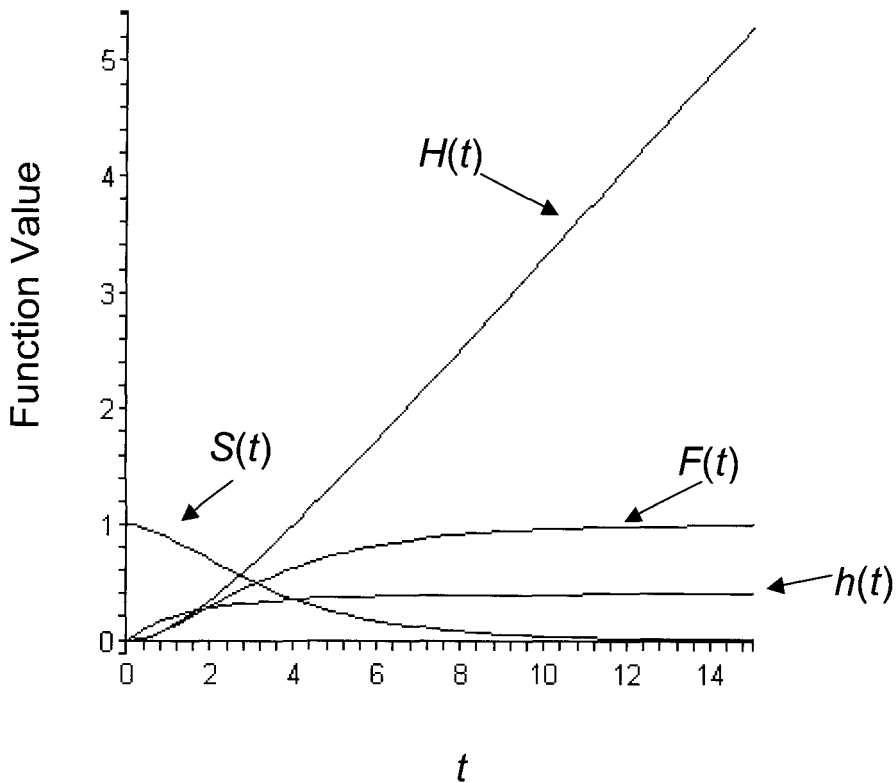
Figure 7.2. Distribution function *F*(*t*), survivor function *S*(*t*), hazard function *h*(*t*), and integrated hazard function *H*(*t*) corresponding with the density function *f*(*t*) of Figure 7.1.

to estimate likelihood of failure (e.g., of a refrigerator or a person [i.e., likelihood of death]) within the next small interval, assuming that failure has not occurred up until that time. These functions, as derived from $f(t)$ in Figure 7.1, are presented in Figure 7.2.[3]

The capacity index specifically exploits $h(t)$ and its denominator, $S(t)$. Note first that $h(t)$ is affiliated with the concept of power in physics (Wenger & Townsend, 2000). It tells us the momentary intensity of a system's work potential and stipulates the immediate pressure toward the state transition of a process, from that of incompletion to completion. It is nevertheless a transitory function of time and therefore difficult to estimate empirically. An index summarizing the collective momentary intensities over the continuous time interval t, however, is $H(t)$. Mathematically, this index is the definite

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[3]Additional explication of these functions, from the standpoint of clinical science, were presented by Neufeld (1998).

integral of $h(t')$ between 0 and t, $\int_0^t h(t')dt'$ (see Figure 7.2). Just as work and energy in physics are associated with a summing or integration of power over a time interval, we can think of $H(t)$ as "energy expenditure" in cognitive operations (Townsend & Ashby, 1978, 1983). As an aggregate, its empirical estimation necessarily is more reliable than are approximations of its infinitesimal constituents $h(t')$. It will turn out that the relation of this integral to the empirically accessible $S(t)$ further increases the appeal of this measure.

The desired $H(t)$ is derived from $S(t)$ as follows. Because $S(t)$, by well-established probability theory, is equivalent to $e^{-H(t)}$, $H(t)$ is simply $-\ln[S(t)]$, where $\ln(x)$ stands for the so-called Naperian or natural logarithm of x. It can also be written as $\log_e(x)$. Consequently, an estimate of $H(t)$, denoted $\hat{H}(t)$, is supplied by $-\ln[\hat{S}(t)]$, where $\hat{S}(t)$ is a sample estimate of $S(t)$.[4] Owing to this composition, then, $\hat{H}(t)$ represents a mathematically principled confluence of two things: (a) the computational tractability and stability of statistical estimation bestowed by data aggregation and (b) the full salvaging of inferences originating with the preaggregate data format (Neufeld & Gardner, 1990).

Observe in passing that $H(t)$ can serve as a characterization of decline in task performance efficiency, historically of considerable interest to clinical scientists (see Maher, 1966, chap. 1). Wishner (1955), for example, conjectured that an earmark of psychopathology is a reduction in the expenditure of energy consummating a task at hand, relative to the total energy laid out during the task's transaction (see also George & Neufeld, 1985; Neufeld, 1990; Nuechterlein & Dawson, 1984). Reduced efficiency, in this view, is tantamount to a lower ratio of work accomplished to total resource investment. The value of $\hat{H}(t)$ obviously would make for a rigorous estimate of the numerator of this ratio, at least in the case of cognitive performance.

The capacity index in turn enters into two composite indexes of comparative capacity, CR and $C_o(t)$. CR provides a general estimate of inequalities in capacity across conditions of performance and/or groups. Whereas CR is a versatile measure that expresses capacity differences generally, $C_o(t)$ does so in liaison with specific increments in task load (detailed later). Coupled with an experimental paradigm for which it was expressly developed, this coefficient measures the change, if any, of capacity as workload is varied. Both of these composite indexes, moreover, can monitor comparative capacity repeatedly over time t.

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[4]Further appreciation of this relation is available from the following explication of $H(t)$ (Townsend & Ashby, 1983, pp. 26, 27). $H(t) = \int_0^t H'(t')dt'$, where $H'(t') = d[-\ln(S[t'])]/dt' = d[-\ln(1 - F(t'))]dt'$, which by the chain rule is $f(t')/[1 - F(t')] = h(t')$.

These composite indexes, as will be seen, apply in somewhat different circumstances, depending on the paradigm and research questions involved. The CR is simply the ratio of $\hat{H}(t)$ obtained for one performance condition or designated group to that of a counterpart. We now explicate its application to the analysis of processing among stress-susceptible, anxiety-prone individuals.

PARADIGM, DATA, AND APPLICATION OF $H(t)$ AND THE CAPACITY RATIO TO HYPOTHESIZED STRESS-SUSCEPTIBILITY EFFECTS ON COGNITIVE PROCESSING

Vulnerability to stress activation has predictable effects on capacity to process visual stimuli and to strategically organize available capacity resources. We develop these points through use of CR, and so we begin by laying out the essential experimental paradigm used to illustrate such application. The resultant data and their organization for accommodating CR are then described. Following these descriptions are specific hypotheses about stress-susceptibility effects as translated in terms of CR. Complementing the subsequent implementation of CR is a section on selected analyses that entail a specific theoretical distribution for processing latencies. This extension elucidates further the nature of CR against this distributional backdrop and indicates additional nuances of formally defined processing capacity.

Note that $H(t)$, and hence CR and $C_o(t)$, are "distribution general" in that they require only that $f(t)$ be a continuous function of t. That is, their meaning is not predicated on a specific shape of the operative distribution, as defined by a particular composition of $f(t)$. Nevertheless, if a specific version of $f(t)$ makes for a parametric distribution that reasonably conforms to empirical observations, then other glimpses into processing operations may be forthcoming. Included are certain angles on the workings of $H(t)$. In addition, parameters of a tenable version of $f(t)$ can naturally align with clinically significant constructs, affording substantively meaningful analyses and associated predictions. In the present case, the tenable distribution happens to be a simple but useful one, the exponential (e.g., Evans, Hastings, & Peacock, 2000).

Paradigm

The following paradigm was used by Jetté (1997) in formally modeling effects of white noise stress and stress susceptibility (physical danger–discomfort trait anxiety) on visual information processing. It was closely fashioned after those of prominent studies of auditory noise effects on light-

flash detection (Hockey, 1970a, 1970b). These studies produce data amenable to stochastic mathematical modeling of capacity deployment (Neufeld, 1996), implicating substantive issues of visual attention in the company of (noise) stress (Broadbent, 1971).

The participants observed an array of six lamps. Two lamps were positioned beside each other toward the center of the visual array, and four were positioned peripherally, two on the left and two on the right of the central region; a light signal emanated from one of the lamps on each trial. Instructions were to press with the left index finger the button on a six-button response panel corresponding to the location of the light, as soon as it appeared. The light signal remained on pending the correct button press.[5]

During the performance of light detection, participants engaged in a pursuit-rotor task with the right hand. This task entailed keeping an L-shaped stylus on the bright spot of a rotating disk. Although presented as the main task, pursuit-rotor activity was incidental to actual theoretical and empirical purposes; in essence, it provided for a common direction of gaze. As in previous work (Forster & Grierson, 1978; Hockey, 1970a, 1970b), rotor speed was calibrated to ensure performance of approximately 65% on target.

The performance measure of principal interest was latency of response to register light appearance. Half of the participants in each anxiety group (i.e., 23 in each condition out of a total of 46 in each group), described below, experienced an even distribution of light signals across the six lamp positions, specifically, 48 in each (unbiased distribution condition). For these participants, the central region produced one third of the total number of signals (96 central and 192 peripheral). For the other half of the participants, each central position produced 96 signals, and each peripheral position produced 24 signals, with two thirds of the signals in the central location (biased distribution condition).

The tasks were performed amidst intermittent 1-second bursts of white noise, delivered through headphones on average every 8 seconds, and always outside the light-signal intervals (Poulton, 1977). There were three levels of intensity: (a) 35 dbA, (b) 88 dbA, and (c) 100 dbA sound pressure level at the ear. Noise levels were evenly dispersed with respect to light signals in the respective spatial locations, and the order of prevailing levels was balanced across participants within each group–condition combination. Participants were 92 right-handed male undergraduates—right handed to reduce individual differences in manual dexterity aspects of performance and male because of documented sex differences in stress response (Neufeld, 1978).

Stress susceptibility was psychometrically identified using the physical danger portion of the Endler Multidimensional Anxiety Scale (Endler,

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[5]Methodological details, otiose with respect to the present exposition, are available in Jetté (1997; see also Hockey, 1970a, 1970b).

Edwards, & Vitelli, 1991). The scale taps respondent apprehensiveness and perceived sympathetic reactions to physical danger, discomfort, or pain. Psychometric properties were enumerated by Endler et al. (1991), and suitability to the present investigative context has been well established (Lefave & Neufeld, 1980; Neufeld & McCarty, 1994). Participants were separated by whether their scores were in the upper (more stress susceptible) versus lower (less susceptible) half of the distribution. Within each division, half of the 46 participants were randomly assigned to the biased signal distribution, and the remainder were administered the unbiased distribution.

Before arranging data to facilitate calculation of $\hat{H}(t)$ and CR, each value was adjusted to throw into relief signal-processing aspects of latency. Note that collateral operations contributing to observed latencies, necessary for task transaction but not deemed to be part and parcel of the focus of modeling, are labeled *base processes*. For example, if memory search were of primary concern (see the section entitled Distribution Properties and Their Roles in Defining the Capacity Index: $H(t)$, above), probe item encoding would be considered a base process. Other base processes would include those involved in translating the results of memory search (probe item present–absent) into the corresponding response (yes–no) and registering it. Apropos of the present paradigm, base processes arguably involve mainly those of converting the result of signal processing into the corresponding location on the response panel and pressing the button (for an elaboration of methods for dealing with base processes, see Townsend & Nozawa, 1995; Townsend & Wenger, 2004a). Thus, estimated duration of response processes was subtracted from each measured response time. The estimate was 552 milliseconds, based on Townsend (1984), a value that turns out to be close to 514 milliseconds, as estimated independently by Bricolo, Gianesini, Fanini, Bundesen, and Chelazzi (2002).

The adjusted latency for correct responses (>95% throughout and not aligned with latency in any way that would undermine inferences from the latter) was aggregated across the group of 23 participants within each stress-proneness/signal-distribution combination. In turn, the data were separated according to central–peripheral regions of signal presentation and prevailing noise level. Latencies were partitioned into bins corresponding to times of 0–600 milliseconds, 600–800 milliseconds, 800–1,000 milliseconds, 1,000–1,200 milliseconds, and >1,200 milliseconds. (The boundary of 600 milliseconds was based on an arbitrary precedent of Hockey [1970a]). Thus, of the total number of trials per group, 736 were available per noise level for the central region under the unbiased distribution, and likewise for the peripheral region under the biased distribution; 1,472 trials per noise level in turn were available for the central and peripheral regions under the biased and unbiased distributions, respectively. Bin entries comprised the

proportions of total adjusted latencies falling into the successive intervals, computed separately for each region and noise level, within each stress-proneness/signal-distribution group.

Aggregation of data across participants within these groups was undertaken in the interests of stability of modeled data and attenuation of model-exogenous noise (e.g., J. R. Carter & Neufeld, 1999; Neufeld & McCarty, 1994). To ensure that resulting data profiles of bin proportions did not conflate systematically differing individual profiles, we used coefficient alpha to estimate profile homogeneity. Accordingly, the computation $1 - (MS_{participants \times bins})/(MS_{participants})$ (Hakstian & Whalen, 1976) was replaced with $1 - (MS_{participants \times bins})/(MS_{bins})$, affording both statistical and interpretative validity (Neufeld & McCarty, 1994; cf. Schmitt, 1996). Data collectives submitted to modeling were verified as representative of their constituents, because alpha estimates ranged from .97 to .99. (Tactics to avoiding artifacts arising from data aggregation are discussed in more detail in this volume's Introduction; see also chaps. 1 and 4, this volume.)

Hypotheses

Hypothesized patterns of CR, as applied to the present data, stemmed from previous formal analyses of stress and stress-susceptibility effects on cognitive performance (Neufeld, 1996; Neufeld & McCarty, 1994). The set of hypothesized patterns now briefly is summarized, followed by the representative application of CR to their investigation.

First, visual-search processing capacity[6] is expected to increase with noise levels, albeit more so with respect to central signal location. Second, stress susceptibility is expected to be identified with diminished visual-search processing capacity. Remaining with stress susceptibility, the third expected pattern entails strategy in deploying available capacity. Stress susceptibility is deemed to impair the advantageous appropriation of resources to display regions, as dictated by target occurrence and task requirements. Investigation of the third hypothesized pattern is described in detail, because of the three, it involves the most comprehensive set of CR procedures.

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[6] Inferences are restricted to visual-search performance, in light of the concurrent pursuit-rotor task. Stress-susceptibility differences in processing capacity applied to this task, making for an equal or possibly greater overall capacity resource pool among the more stress-susceptible individuals, cannot be ruled out. Such a possibility nevertheless is unlikely, considering the characteristics of the pursuit-rotor task, as described above. Moreover, the visual-search results from which the present hypothesis arose (Neufeld & McCarty, 1994) did not entail a concurrent psychomotor task. Postulated mechanisms of diminished processing capacity among more anxiety-prone individuals have been enumerated by Neufeld (1996) and by Neufeld and McCarty (1994).

Application of Capacity Ratio

Computed values of CR essentially endorsed expectations in each case. Specifically, noise elevation generated higher values of $H(t)$ for both stress-prone groups, especially when increasing from low to medium levels, this effect being most apparent for the central region and among participants experiencing the centrally biased signal distribution. Corresponding values of CR comprising $\hat{H}(t)_{lower\,noise\,level} / \hat{H}(t)_{higher\,noise\,level}$ were generally less than 1.0 and were homogeneously so under the above conditions. The disproportionate increase associated with the central region under biased conditions, notably for the low versus medium noise levels, corresponded to lower values of the above CR when computed for the central versus peripheral region. That is, $CR_{central} / CR_{peripheral}$, the "second-order CR," was less than 1.0. Computational details were, to all intents and purposes, identical to those addressing stress-susceptibility and strategies of capacity allocation, below.

The pattern of noise-related capacity changes was accordant with a noise-induced increased tendency to focus resources toward more important task features. Such a pattern has been proposed as a mechanism of selectively improved performance under noise conditions (Broadbent, 1971; Hockey, 1970a, 1970b). Other theoretical accounts of noise-associated capacity increase are available from a stochastic-modeling platform (Neufeld, 1994, 1996).

Note that the present set of inferences stemming from the application of CR were compatible with those from generic analyses of the adjusted latencies (e.g., significant analysis of variance higher order interaction among noise levels, signal distribution, and central–peripheral region, $p < .05$; cf. chap. 2, this volume, regarding instances of opposing inferences from formal modeling and generic analyses). A certain overlap notwithstanding, formal modeling stands to furnish the informational added value emanating from a disciplined mathematical abstraction of the process tenably responsible for the data summaries to which the generic analyses are applied. Added value includes interpretative insights, data-analytic extensions, and paradigmatic innovations, illustrated in this chapter and throughout the volume at large.

Table 7.1 presents proportions of adjusted observed latencies in the respective interval bins. Also listed are the estimated values of $H(t)$, obtained as $-\ln[\hat{S}(t)]$, where $\hat{S}(t)$ is equal to 1 minus the cumulative bin proportions; for example, $1.890 = -\ln(0.151) = -\ln[1 - (0.736 + 0.113)]$.

Lower values of $\hat{H}(t)$ accompanied higher stress susceptibility throughout. This result is exemplified in Table 7.1 for performance under medium noise and centrally biased signal frequency. (The full set of results is available in Jetté, 1997). On top of diminished capacity overall was evidence of its less advantageous deployment with respect to task conditions (in line with the third prediction, see Hypothesis section). In particular, adjusting avail-

TABLE 7.1
Observed Bin Proportions, Estimated Survivor Functions $\hat{S}(t)$,
and Capacity-Index $\hat{H}(t)$ Values for Each Group Under Medium
Noise Level and Centrally Biased Signal Distribution

	Bin interval (milliseconds)			
Location estimates	0–600	600–800	800–1,000	1,000–1,200
Low stress susceptable				
Peripheral				
Observed proportion	0.736	0.113	0.055	0.035
Estimated survivor function	0.264	0.151	0.096	0.061
Capacity index	1.332	1.890	2.343	2.797
Central				
Observed proportion	0.832	0.090	0.038	0.018
Estimated survivor function	0.168	0.078	0.04	0.022
Capacity index	1.784	2.551	3.219	3.817
High stress susceptible				
Peripheral				
Observed proportion	0.72	0.113	0.053	0.045
Estimated survivor function	0.28	0.167	0.114	0.069
Capacity index	1.273	1.790	2.172	2.674
Central				
Observed proportion	0.737	0.131	0.048	0.029
Estimated survivor function	0.263	0.132	0.084	0.055
Capacity index	1.336	2.025	2.477	2.900

able processing resources according to signal frequencies in the visual array stands to improve performance. The centrally biased distribution should draw more processing capacity to that region, and the opposite should be true for the unbiased distribution. Frequency-based strategy of allocation was more pronounced for the participants with lower stress proneness, as educed by $\hat{H}(t)$ and CR. The results for the biased distribution under the medium noise level provide a representative example of this pattern (see Table 7.1). Apropos of analysis of variance on the latency distributions, this representative selection is analogous to using a simple first-order interaction to dissect an obtained significant second-order Stress Proneness × Distribution Bias × Display Region interaction ($p < .05$ in the present case). Values of $\hat{H}(t)$ were greater for central than peripheral regions for both lower and higher stress-susceptibility groups, leading to $CR = \hat{H}(t)_{peripheral}/ \hat{H}(t)_{central} < 1.0$. Disproportionately greater deployment of processing capacity to the central region by the participants with lower susceptibility corresponded to values less than 1.0 for the second-order CR, $CR_{lower\ stress\ susceptibility}/ CR_{higher\ stress\ susceptibility}$; that is, more capacity was devoted to the central versus peripheral region for both groups, resulting in $CR < 1.0$ for each; the effect, however, was more pronounced for the low-susceptibility group, leading

to their greater deflation of CR. Actual values of this second-order CR, corresponding to the respective bins in Table 7.1 (proceeding from left to right), are .78, .84, .83, and .80. The question of which group evinced a division of taskwise capacity closer to the optimum is examined in the following section.

Parametric Extension

Previous analysis of secondary data from experiments using paradigms similar to the present one (Hockey, 1970a, 1970b) encouraged consideration of the exponential distribution as a theoretical account of processing latencies (Neufeld, 1996, adapting Compound Parallel Model 1 of Townsend & Ashby, 1983, chap. 5). This distribution's density function is ve^{-vt}, where v is the rate of completion of a processed element (e.g., region of a visual array) and t is the elapsed time since processing commencement. The distribution function $F(t)$ is $\int_0^t ve^{-vt'} dt' = 1 - e^{-vt}$ and the survivor function $S(t) = e^{-vt}$, implying $-\ln[S(t)] = vt$. Dividing the density function by the survivor function, the hazard function $h(t)$ is seen to be equal to the rate parameter v and constant across all t. Finally, the mean of the distribution is $1/v$, and its variance is $1/v^2$.

The capacity index can be examined against the backdrop of this distribution. Note that the validity of this application is supported by multiple tests on empirical fit, applied both to the current binned proportions and to overall latencies. Probabilities for chi-square tests of goodness of fit ranged from .30 to .99, with an average of .71. Thus, results were solidly within the envelope prescribed by the hypothesized distribution.

The maximum likelihood estimate (MLE) of the exponential distribution's parameter v, MLE(v), based on a set of adjusted latencies of size N is $N/\sum_{i=1}^{N} t_{adj,i}$, or simply the reciprocal of the mean. This estimate entered into the above goodness-of-fit tests. Alternatively, $S(t)$ spawns its own version of MLE(v), specifically, $-\ln[\hat{S}(t)]/t$, or $\hat{H}(t)/t$, which shows $\hat{H}(t)$ to be a scaled maximum-likelihood estimator of capacity in the case of this distribution. Moreover, where the respective elements (regions) are processed in parallel, with each region's latencies independent of the other's, the estimated collective taskwise capacity is simply the sum of the individual estimates, in this case, $1/t[\hat{H}(t)_{central} + \hat{H}(t)_{peripheral}] = v_{central} + v_{peripheral}$ (Townsend & Ashby, 1983, p. 249).

Normative and Descriptive Models

The present parametric distribution affords the aforementioned observations not only on the capacity index but also on selected extensions. The

slant on capacity endowed by this distribution bears on certain issues of potential import in clinical cognitive science, in this case involving the optimal allocation of taskwise capacity to central and peripheral regions of a visual display. Optimal division of processing capacity can be viewed as the most efficient division of attention in the present type of task, where vigilance for the occurrence of an environmental event is called for. The strategy that maximizes performance can be indicated by linking up the performance model and prevailing task characteristics.

Such a computed optimum is considered to be defined by a *normative model*, as identified with statistically prescribed idealized performance. A *descriptive model* depicts how individuals actually perform the task (Edwards, 1998). The descriptive model's capacity allocation for each of the low and high stress-susceptible participants can be compared for its proximity to optimal capacity allocation as computed from the normative model.

In the present context, optimal capacity deployment may be viewed as that resulting in the minimum latency for registering the appearance of a signal. A complementary angle deals with allocation that maximizes detection, given a specific time interval of signal duration t. The latter orientation coincides with the present overall tack to capacity measurement, because detection failure can be modeled in terms of the survivor function $S(t)$. This direction of analysis is developed using a signal interval of 600 milliseconds.

The current proportions of adjusted latencies equal to or less than 600 milliseconds now stand as a surrogate for the rates of detecting signals lasting only 600 milliseconds (the signal duration used in Hockey, 1970a), even though they actually remained on pending a response (as in Hockey, 1970b). Estimates of v for this analysis are obtained as $-\ln[\hat{S}(t)]/t$, where $t = 600$, and $\hat{S}(t)$ is $1 -$ (proportion of adjusted latencies equal to or less than 600 milliseconds). Results from this analysis are depicted graphically in Figure 7.3; reference to the figure may aid in following the steps described below.

We let the probability of a signal occurrence in the region with the higher frequencies be denoted w_H, and that in the lower frequency region be $w_L = 1 - w_H$. Processing capacity deployed to the w_H region is denoted v_H, and that to the w_L region is denoted v_L. Taskwise capacity is estimated as $v_H + v_L = c$. The probability of detection failure is

$$w_H S_H(t) + w_L S_L(t), \tag{7.1}$$

where, in the present instantiation, $S_H(t) = e^{-v_H t}$ and $S_L(t) = e^{-(c - v_H)t}$. After substituting these expressions in Equation 7.1, and applying the usual operations of differential calculus to find a minimum, Equation 7.1 is shown to be minimized with respect to v_H when the latter is equal to

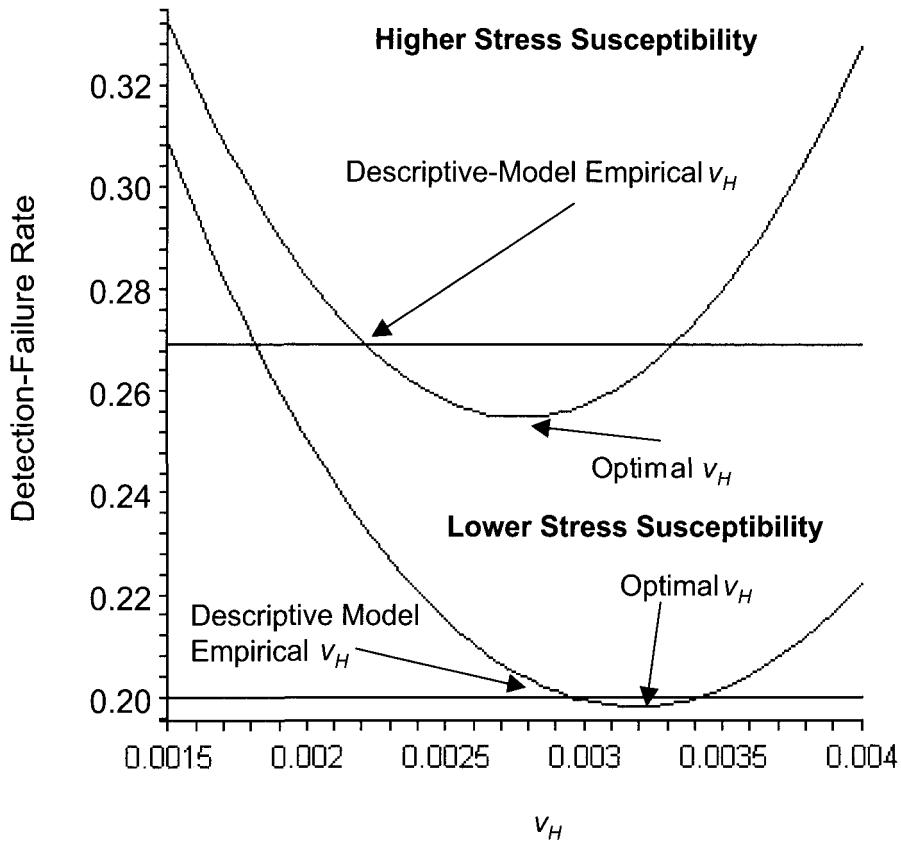$$1/(2t)[\ln(w_H) - \ln(w_L)] + c/2. \tag{7.2}$$

Figure 7.3. Detection-failure curves for individuals higher and lower in stress susceptibility. Higher elevation of the "higher stress susceptibility" curve reflects diminished taskwise capacity. Optimal values of v_H, as prescribed by the normative model, are those minimizing detection failures. Empirical estimates of v_H, for the descriptive model addressed to actual performance, correspond to the left-hand intersections of the curves with the horizontal lines, the latter in turn depicting resulting levels of empirical detection-failure rates.

A representative example of the computations for the normative and descriptive models is supplied by the combination of performance conditions made up of the centrally biased signal distribution delivered amidst a medium noise level. With $t = 600$, and $w_H = .67$ (corresponding to the central region light signal frequency), c for the lower susceptibility participants is estimated to be .00519, and optimal $v_H = .00318$. Corresponding values for the more highly susceptible individuals are .00435 and .00276.

As for the descriptive model, the value of v_H estimated for the lower susceptible participants is .00297, lower than the optimum by .00021, and that for the more highly susceptible counterparts is .00222, a departure from the optimum of .00054. By the normative model, optimal allocation for the

lower susceptible individuals would result in a detection-failure rate of .198, close to the observed value of .200. If their capacity were equally divided between regions, the detection-failure rate would be .211. Optimal allocation for the more highly susceptible individuals would produce a detection-failure rate of .255, the observed value being .269. The amount corresponding to hypothetical equal allocation is .271. The increase in optimal allocation detection failure from .198 to .255, when going from the lower to more highly susceptible individuals, results from the lower value of c for the more highly susceptible group.

The optimal proportion of c to be dispatched to the central region is .6127 for the lower susceptible group. The estimated actual proportion is .5722, a difference of .04. For the more highly susceptible group, the calculated optimal proportion is .6348, compared with the empirical estimate of .5106, for a difference of .1242. Detection times for the central region, obtained as $1/v_H$, are 337 milliseconds for the lower susceptibility group, compared with 450 milliseconds for the more highly susceptible group; corresponding values for the peripheral region are 450 milliseconds and 469 milliseconds. Finally, note that a similar set of computations are available with respect to optimal division of capacity and performance maximization in terms of minimized processing latencies, rather than maximized light detection at time t (Neufeld, 1996).

To summarize, the present extension throws light on $H(t)$ according to its operation within a tenable parametric distribution. The parametric implementation of $H(t)$ offers up a quantitative gold standard against which measured performance can be assessed. It does so explicitly in terms of efficiency in adapting processing resources to the presenting task structure. Stress proneness associated with trait anxiety not only diminishes capacity to transact a given cognitive task (cf. Mogg, Bradley, Williams, & Mathews, 1993) but also compromises the interplay of remaining resources with task exigencies. Quantification of relations between task properties and processing capacity evidently yields pellucid mathematical expressions of selected cognitive vulnerabilities. Potential consequences, in the form of compromised negotiation of cognition-intensive coping, in turn have been drawn out from a nonlinear dynamical-systems ("chaos-theoretic") perspective in Neufeld (1999).

ANALYSIS OF MEMORY SEARCH IN SCHIZOPHRENIA

We turn now to the illustrative application of $C_o(t)$ to clinical data. A cognitive function that appears to have been spared among individuals with schizophrenia is that comprising the examination of material held in memory, a function known as *memory scanning*. In a typical memory-search

task (Sternberg, 1975), for example, this function entails the search through memory for the presence of a visually presented probe item (see description in the Distribution Properties and Their Roles in Defining the Capacity Index section). Speed and accuracy of memory scanning evidently escape unscathed.[7] The collateral process of probe item encoding, however, decidedly is affected, an observation that is taken up further in chapter 5 of this volume.

Identifying and deciphering the nature of spared as well as affected aspects of cognition are important to producing a balanced profile of cognitive functioning characterizing a disorder. The discerned set of strengths and weaknesses arguably contributes to a fuller understanding of the symptom picture (George & Neufeld, 1985; Neufeld, Vollick, & Highgate-Maynard, 1993).

Also afforded is the possibility of exploiting apparent strengths in the service of intervention (cf. Penn & Spaulding, 1997). The capacity coefficient $C_o(t)$ can be used to penetrate capacity properties of cognitive processing in general and is applied here to memory-search operations deemed to be held in common by patients with schizophrenia and control participants. We again emphasize the much greater power and dynamic processing detail available with the current methods.

Paradigm

A study by Highgate-Maynard and Neufeld (1986) extended typical memory-search methodology by incorporating methods emanating from Paivio's (1986) dual-coding theory. Individuals with schizophrenia and control participants indicated "as quickly and accurately as possible" whether the real-life size—"overall volume"—of a presented item (a probe item comprising either an object or animal) was similar to that of a member of a previously memorized set of items (memory set). The number of items in the memory set (*memory-set size*) ranged from one to four. Each memory set of a given size was composed of its own set of items (e.g., breadcrumb, coffeepot, and bed for a set size of three; dot, teapot, dresser, and airplane for a set size of four), which in turn stayed the same for that set size throughout the experiment (known as a *fixed set procedure*). Correspondence versus absence of the probe's size properties to those of one of the members of the memory set (positive vs. negative trials) was balanced with respect to memory set size. The 4×2, Set Size × Positive Versus Negative trial, combinations were presented in random order. For reasons tangential to

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[7] As with tenability of a parametric distribution according to goodness-of-fit testing, above, this inference currently is based on repeatedly negative statistical findings and stands to be supplemented with other recommended methods for "accepting the null hypothesis" (Cohen, 1988, pp. 16, 17).

memory scanning per se (Neufeld et al., 1993), half the participants in each group were presented with similar-sized drawings of probe items, whereas the other half were presented with their names.

Scanning memory-held items for the presence of the probe's size properties was considered to be comparatively taxing. It required comparison between the probe and memory-held items' overall volume, as set against subjective criteria of similarity in this property (Hockley & Murdock, 1987; Wright, 1977). Size attributes of items in the memory set were spaced such that the means of their normative-size ratings (Paivio, 1975) were at least 2 standard deviations of their Thurstonian discriminal-difference size dispersions apart (practically, at least 2 standard deviations of the distribution of difference scores between their normative size ratings; Highgate-Maynard & Neufeld, 1986). Responses were designated as correct or incorrect on the basis of whether they conformed to the following criteria for positive and negative trials. Negative trials, the correct response to which was a "no" button press, meant that the probe item's size did not resemble that of a memory-set item. Here, the probe item's mean real-life size rating was at least 1 standard deviation of the Thurstonian discriminal-difference dispersion from the normative mean rating of each item in the memory set. Positive trials, the correct response to which was a "yes" button press, were those where the mean of the probe item, and that of a memory-set member were, to all intents and purposes, identical. Practice trials, ensuring familiarity with task requirements and the nature of correct responding, were similar in number for each group.

Further specifics, including those surrounding provision for potentially confounding clinical and demographic variables and ascertainment of the viability of the paradigm for each diagnostic group of participants (e.g., applicability of normed item properties to each one), were detailed by Highgate-Maynard and Neufeld (1986) and were summarized by Neufeld, Carter, Boksman, Jetté, and Vollick (2002). Considering the current emphasis on latencies, we should emphasize that error rates were comparable across groups and did not contribute to latencies in any confounding way.

$C_o(t)$ in Light of the Memory-Search Paradigm

In explicating $H(t)$ and CR (see p. 210) we followed distribution-general developments with their instantiation in the exponential distribution. Conversely, it will be advantageous to launch developments of $C_o(t)$ from a parametric-distribution platform applicable to the results from this study. Doing so illustrates how the specific capacity properties embodied in the parametric distributions are expressed in terms of $C_o(t)$. Operations of these coefficients, illustrated in the given parametric case, nevertheless are distribution general.

The model applicable to memory search for this task, known as an *independent parallel model with moderately limited capacity* (IPMLC), was presented in Townsend and Ashby (1983). The rationale for its claimed viability here was detailed by Neufeld et al. (1993). Note that a stochastic model of parallel processing specifies that items are commenced simultaneously but that individual item completions are staggered stochastically across time. In the present model, memory-set items are processed in parallel, each completion is exponentially distributed with rate parameter v_n (see the description of the exponential distribution, above), and each is independent of any other completion. The capacity available to each item v_n nevertheless is partly degraded as the set size n increases.[8]

If capacity were unlimited rather than moderately limited, then the rate at which an individual item is processed, v_n, would be unaltered as n increases. The rate applicable to a single item being processed in isolation, $n = 1$, would remain in effect even as items are added to the memory set, $n = 2,3,4, \ldots$ (in the present case, n's maximum value being 4). Thus, $v_1 = v_2 = v_3 \ldots$. It is interesting that with parallel processing of a set size of n and unlimited capacity, times for the first item completion remain exponentially distributed, but with the rate parameter applicable to the first completion of the n-item set being $\sum_{i=1}^{n} v_n = n v_n$ (see Townsend & Ashby, 1983, pp. 90, 249, and the Parametric Extension section). This *independent-parallel unlimited capacity* (IPUC) model furnishes a benchmark for synthesizing IPMLCs' capacity attributes in terms of $C_o(t)$. Transdistribution properties of the IPUC processing architecture also provide a benchmark in the use of $C_o(t)$ to assess capacity aspects of examined systems in the distribution-general case, below.

For the IPMLC model, then, the decline in v_n as n increases is expressed as $v_n = v_1 / n \sum_{i=1}^{n} 1/i$, where v_1 is the rate for a single item processed by itself. As n increases from 2 through 4, for example, v_1 is scaled by .75, .61, and .52 to produce v_2, v_3, and v_4, respectively. This system's capacity is moderately limited because the decline in v_n with increasing n is less drastic than for a fixed-capacity system, where $v_n = v_1/n$. As with the IPUC model, the first completion again is exponentially distributed with rate parameter $n v_n$; however, v_n now is that prescribed by the IPMLC model.

The IPMLC model exemplifies certain properties of processing systems that elucidate the functioning of $C_o(t)$. One such property is *channel capacity*. It can be helpful to envision each of the set of n items as having a dedicated processing channel—analogous to a neural circuit but agnostic as to the

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[8]Regarding the representativeness of individuals' memory-scanning performance by aggregated data subjected to modeling, pertinent alpha coefficients ranged from .92 to .94 (see "Paradigm" section).

circuitry involved. Among other variations, channel capacity can be unlimited, very limited, or moderately limited; consider the IPUC, the independent parallel fixed-capacity, and IPMLC models, respectively, described above.

Another concept brought to bear is that of *statistical advantage*. In an independent parallel system, the hazard function $h(t)$ for the next completion of a set of items in progress is the sum of their individual hazard functions. Thus, the instantaneous rate of an upcoming completion, given the continuation of all members of a set, increases with the size of the set. Formally, for n items,

$$h(t)_{min} = \sum_{i=1}^{n} h(t)_i, \qquad (7.3)$$

where $h(t)_{min}$ is the hazard function corresponding to the minimum of the n completion latencies, and $h(t)_i$ is the hazard function for item i, considered in isolation (befitting the independence provision); $i = 1, 2, ..., n$. Replacing t with t' in Equation 7.3 and integrating from $t' = 0$ to $t' = t$, we have $H(t)_{min} = \sum_{i=1}^{n} H(t)_i$. Furthermore, because the survivor function of the first completion $S(t)_{min}$ is equal to $e^{-H(t)_{min}}$, $-\ln[S(t)]_{min}$ is equal to $H(t)_{min}$.

These relations are instantiated in the case where the latencies for each item are exponentially distributed. Recall that with n items being processed independently and concurrently, each with rate parameter v_n, the rate parameter for the first completion is $\sum_{i=1}^{n} v_n = nv_n$, or n times $h(t)$ for the individual item.

A potentially useful, albeit rough analogy to the interplay of statistical advantage and channel capacity entails a set of randomly kinetic billiard balls, as follows. The speed with which the first ball drops into a pocket increases with the number of balls set in motion, roughly expressing statistical advantage. As for capacity limitation, with an increase in the number of balls rambling about on the playing surface, mutual interference, or momentary adverse effects on the playing surface (to stretch the analogy), may impair the balls' movement, prolonging the pocketing time.

We now examine how $C_o(t)$ captures the properties of statistical advantage and channel capacity. Results from applying this coefficient to assess targeted systems must be set against those from a system embodying a referent set of known properties. The IPUC model comes to the fore as the needed benchmark.

Paradigmatic requirements for the application of $C_o(t)$ entail redundant targets, as follows. In the case of visual search, more than 1 item of a visual array—say, 2—would match a previously presented target item. In the

present case of memory search, the real life-size properties of more than one member of the memory set would match that of the probe item, according to the statistical criteria described above. With memory-set sizes n ranging between 1 and 2, on positive trials, there is a match between the probe and a single item, or a pair of memory-set items, respectively. Needless to say, such trials are balanced with randomly interspersed presentations of negative (no-match) trials. Participants are instructed to give a positive response ("yes" button press) if the probe's size properties are matched by those of the single member ($n = 1$), or either member ($n = 2$) of the memory set and to give a negative response otherwise. It is therefore assumed that responding is self-terminating, meaning that on positive trials where $n = 2$, processing ceases and responding occurs on detecting a match to the probe on the part of either member of the memory set. On these grounds, $H(t)_{min}$ is thrown into relief, with respect to $C_o(t)$. Note that for purposes of exposition, the present developments are based on an extrapolation of the actual procedures used by Highgate-Maynard and Neufeld (1986) combined with the IPMLC model inferred from those results.

Now, $C_o(t)$ simply comprises a certain ratio involving capacity indexes $H(t)$. Its numerator comprises $H(t)$ for the redundant-target trials, where both of the pair of memory-set items match the probe, denoted $H(t)_b$. The denominator consists of the sum of $H(t)$ for the single-target trials, or $2H(t)_s$, assuming as in the present case that the single-target distributions are identical. Consequently, $C_o(t)$ becomes $H(t)_b/2H(t)_s$. For the theoretical IPUC system, the survivor function for the first completion, allowing $n = 2$ (corresponding to $S[t]_b$) is $S(t)_s^2$, which in turn equals $[e^{-H(t)_s}]^2 = e^{-2H(t)_s}$. This expression makes $-\ln[S(t)_b] = 2H(t)_s$. The IPUC system thereby furnishes the denominator of $C_o(t)$, which anchors evaluation of the assessed system. The numerator of $C_o(t)$, in turn, is the value for that system of $H(t)_b = -\ln[S(t)_b]$ for the $n = 2$ trials.

If $C_o(t) = 1.0$, the most economical interpretation is that the examined system is one of independent processing and unlimited capacity (although note that some serial systems can mimic—are empirically equivalent to— IPUC systems; see, e.g., Townsend, 1990). If $C_o(t)$ is less than 1, then the examined system's task completion capacity is less than that of an IPUC system, or is one of limited capacity. If, on the other hand, $C_o(t)$ is greater than 1.0, then task-completion capacity exceeds that of the IPUC system, and supercapacity is said to be operative. Note that in practice each term of $C_o(t)$ is replaced by its empirically observed estimate.

Observe that $C_o(t)$ is distribution general. Its computation and interpretation presuppose no specific theoretical distributions, except that they are continuous across t. Second, we have specified that $C_o(t)$ addresses task-completion capacity. Values of $C_o(t)$ departing from 1.0 may indicate any or some combination of properties dislodging the system's capacity from

that of the IPUC benchmark. Values less than 1.0 may signal, for example, a less efficient architecture (e.g., certain types of serial processing), deviation from a self-terminating stopping rule (notably, processing both items when one will suffice; recall that completions are stochastically distributed and therefore not synchronous), or limited channel capacity (reduction in each channel's speed, on concurrent processing). For that matter, one such property may have an elevating effect on $C_o(t)$ (e.g., mutual channel facilitation, as opposed to impedance), only to be overridden by another (e.g., exhaustive item processing).

Conversely, a value of $C_o(t)$ greater than 1.0, a signature of system supercapacity, may bespeak an architecture conducive to faster completions. One such architecture has a coactive, channel-summation parallel structure, whereby the products of channels processing concurrently are funneled into a repository channel, which is responsive to the cumulative output from its tributaries (Townsend & Nozawa, 1995; Townsend & Wenger, 2004a). Another possibility comprises the above mutual channel facilitation within a regular parallel architecture (Townsend & Wenger, 2004b). Clinical examples of supercapacity, and postulated mechanisms of its occurrence, include multidimensional stimulus encoding in schizophrenia (J. R. Carter & Neufeld, 1999) and the enhancing effects of stress on cognitive performance (Neufeld, 1996).

On balance, then, $C_o(t)$ is a mathematically moored, distribution-general coefficient that parsimoniously embodies the key ingredients of system capacity. It incorporates a principled benchmark system and suggests sources of departure of an assessed system in either direction. Moreover, $C_o(t)$ subsumes prominent system-capacity earmarks, known as the *Grice* inequality and the *Miller* inequality (see Townsend & Nozawa, 1995; Townsend & Wenger, 2004b). A comprehensive paradigm simultaneously monitoring $C_o(t)$, and its sources of departure from 1.0, is prescribed in Townsend and Wenger (2004a; this is known as "double factorial technology"; see also Townsend & Nozawa, 1995).

Application of $C_o(t)$ to Results From the Memory-Search Paradigm

Application of $C_o(t)$ to the current IPMLC system unveils the underlying interplay of statistical advantage and channel capacity. Simultaneous monitoring of $C_o(t)$ and the agents of its variation in the case at hand affords appreciation of candidate reasons for its precise value here and elsewhere.

Under the IPMLC model, statistical advantage remains in play, but individual channel capacity is diminished. The estimated value of v_1 in the present case was 1.23 (defensibly common to the clinical and nonclinical groups; Neufeld et al., 1993), the units of measurement now being seconds. As each item's completion latency is deemed exponentially distributed, the

denominator of $C_o(t)$, specified by the IPUC model with $v_1 = 1.23$, is $2H(t)_s = 2[-\ln(S(t)_s)] = 2[-\ln(e^{-v_1 t})] = 2.46t$. Whereas the value of $v_{n=2}$ for the IPUC model remains 1.23, that defined by the IPMLC model is 0.9225. So, the numerator of $C_o(t)$ now is $-\ln[S(t)_b] = -\ln(e^{-2H(t)}) = -\ln[e^{-2(.9225)t}] = 1.8450t$. The resultant value of $C_o(t)$ is thus 0.75.

If the operative system were one of independent processing, and unlimited capacity, the numerator of $C_o(t)$ would be $-\ln[S(t)_b] = -\ln[e^{-2(1.23)t}] = 2.46t$, and $C_o(t)$ would be 1.0. Statistical advantage would be fully realized rather than being somewhat offset through moderately limited channel capacity.

The detraction from statistical advantage of the current moderately limited capacity, however, is less severe than that accompanying fixed capacity. There, the value of $v_1 = 1.23$ would be spread across the two items, resulting in $v_{n=2} = 0.615$, and $C_o(t) = 0.50$. In this case, statistical advantage would be completely offset by channel-capacity limitation.

A value of 0.50 for $C_o(t)$ also would occur if a regular serial architecture were in place (Townsend & Ashby, 1983, pp. 80, 88). Rather than parallel processing, with capacity being split between the two items, processing would begin with one of the items, its rate being 1.23. Statistical advantage no longer is fully offset by channel-capacity limitation. Instead, being intrinsic to parallel processing, it now is absent at the outset.

Values of $H(t) = -\ln[S(t)]$ entering into $C_o(t)$ are plotted in Figure 7.4. That for the IPUC benchmark composes the upper line. An assessed system with like architecture and capacity attributes generates identical values of $H(t)$ for the numerator of $C_o(t)$ (apart from sampling and measurement error), yielding $C_o(t) = 1.0$ throughout the range of t. Note that the constancy of $C_o(t)$ across time t in each of the present cases arises from latencies being exponentially distributed. Values of this coefficient of course can vary across t for other distributions (see, e.g., Wenger & Townsend, 2000).

Values for the IPMLC structure constitute the middle line, and those for independent parallel processing with fixed capacity (IPFC) constitute the lower line. To more closely resemble noise-infiltrated empirical data, each of the latter depictions is perturbed slightly with the addition of random values ranging from −0.05 to +0.05. Values of $C_o(t)$ for the IPUC system should approximate $[2(.9225)]/[2(1.23)] = 0.75$, and those for an IPFC system should approximate $[2(.615)]/[2(1.23)] = 0.50$.

In summary, the coordination of $H(t)$ with the redundant-target paradigm issues in a quantitatively principled measure of capacity of an assessed system, the capacity OR index, $C_o(t)$. The denominator of this index can be assembled from single-target trials so as to express the value that would occur with redundant-target trials, as seen in its numerator, if the system were of an independent parallel architecture with unlimited channel capac-
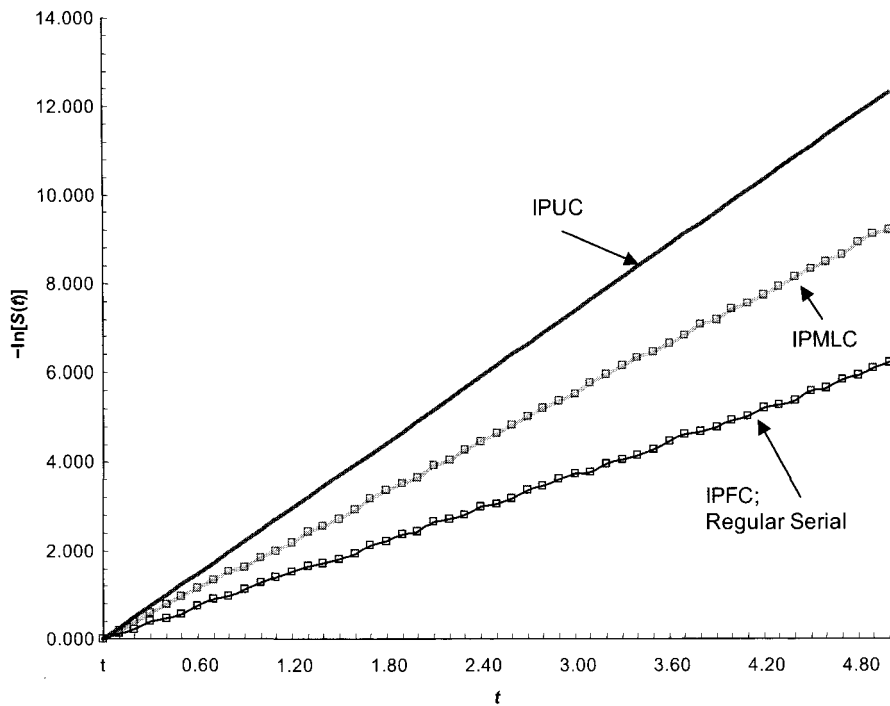
Figure 7.4. Values of the capacity coefficient $H(t) = -\ln[S(t)]$ portrayed for the independent-parallel unlimited capacity model (IPUC) benchmark, and independent parallel model with moderately limited capacity (IPMLC) and independent parallel model with fixed capacity (IPFC; empirically equivalent to standard serial for first-completion time), from $t = 0$ through $t = 5$, with $S(t)$ putatively sampled every 0.1 second. The value for v_1 for each structure is 1.23. Values specified by the IPMLC and IPFC models are randomly perturbed to convey some infiltration of empirical estimates by noise.

ity. Sources of departure from this reference system—channel-capacity limitation in the context of parallel-processing statistical advantage—provide a parametric glimpse into the overall workings of $C_o(t)$. In other words, selected mechanisms of cognitive-performance capacity captured by $C_o(t)$ are delineated as they take shape in the particular parametric case.

Some Clinical Inferences

Features of processing architecture affecting $C_o(t)$ stand to be shared by patients and control participants, because processing architecture in and of itself tends to remain intact with disorder (Neufeld & Broga, 1981; Neufeld et al., 2002; cf. Townsend et al., in press). Certain properties endowed by a given architecture therefore are no less present if its bearer is experiencing schizophrenia than otherwise. In the case at hand, such

properties include statistical advantage accruing to an independent parallel structure.

Channel capacity conceivably could suffer with disorder. In the present instance, however, moderately limited capacity defensibly is shared by both groups. The absence of disproportionate channel-capacity limitation is reminiscent of findings for schizophrenia more generally, when capacity has been delineated within a formal theoretical framework (J. R. Carter & Neufeld, 2006; Neufeld et al., 1993; cf. chap. 5, this volume).

Although not that of unlimited capacity or supercapacity, the speed of ascertaining the status of an encountered stimulus over that of a fixed-capacity system stands to convey potentially important adaptive advantage in self-maintenance and meeting of environmental demands. Moreover, such comparative advantage potentially is compounded as memory-scanning requirements mount up in scanning-intensive tasks. It also arguably is ramified according to the constellation of other transactions contingent on the product of memory scanning (e.g., organizing a response appropriate to the memory-conveyed properties of a person, object, or event; cf. Schweikert, 1989; Wenger & Townsend, 2000). Again, to the degree that the present formulation can be brought forth, the temporal advantage imbued by an IPMLC structure over that of others, such as an IPFC or regular serial structure, is not lost with schizophrenia. This observation is in accord with other findings of intact memory search accompanying this disturbance (reviewed in Neufeld & Broga, 1981; see also Neufeld, 1991).

CONCLUSION

Cognitive processing capacity is a complex construct. Its meaning and measurement in a given application are intractable without the qualifications and constraints imposed by formal theory. Overall capacity to perform a cognitive task is available as the capacity index $H(t)$. Comparative taskwise capacity across performance conditions and/or groups can be evaluated using CR. Values are readily computed and have wide application.

The Capacity OR Coefficient $C_o(t)$ likewise is readily computable. It operates in lockstep with a collateral paradigm and assesses a submitted system against a standard of known architecture and channel-capacity characteristics. A system's unlimited capacity, limited capacity, or supercapacity depends on the absence, or the direction, of departure from the pivotal value of 1.0. Because $C_o(t)$ invokes a system with defined properties, candidate sources of $C_o(t)$'s value for the examined system are forthcoming.

A more recent capacity coefficient, complementing $C_o(t)$, is the Capacity AND Coefficient, $C_a(t)$ (Townsend & Wenger, 2004b). This coefficient resembles $C_o(t)$ in its computation and, like $C_o(t)$, prescribes an associated

paradigm as well as the IPUC system as a benchmark. Its focus, however, is on exhaustive processing (as with completion of both items of a two-item memory set or visual array). Experimental trials of principal interest therefore are negative trials, whereby a target is not present in the memorized or visually inspected item set. Coupled with $C_0(t)$, this coefficient increasingly should make for a comprehensive picture of the operative system and act as a consistency test (Meehl, 1983) for inferences drawn from $C_0(t)$.

The capacity measures presented here inform the interpretation of generic data summaries, such as moments and other summary statistics. For example, allowing that reaction time reflects a continuous underlying latency distribution, mean reaction time is the integral from zero to infinity of the distribution's survivor function. The survivor function at time t is simply e exponentiated by -1 times the integral of the hazard function, taken between 0 and t. The hazard function, in turn, is explicitly tied to the concept of processing capacity. In this way, the mean reaction time has its own roots in an integrand that is elemental to formal capacity measures. Even the interpretation of a mean reaction time therefore is embellished by unveiling its dynamic stochastic composition.

The measures presented here clearly spring from decidedly formal theory. Experimental paradigms and forms of data partitioning are prescribed by the theoretical developments. Such results are in the spirit of theory-determined rather than off-the-shelf measurement (McFall & Townsend, 1998; Meehl, 1978), and they are in accord with the Einsteinian edict that "useful theory indicates where to look and provides a means of interpreting what is seen." The realization of dynamic stochastic properties in theory and measurement should advance assessment methodology for prominent concepts in clinical science as it has in other areas of psychology and older disciplines.

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