Modeling Stress Effects on Coping-Related Cognition.

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Introduction.

Explaining and measuring effects of psychological stress[1] on cognitive functioning is considered to be of considerable importance in the field of psychological stress and coping. Much coping is cognition intensive, comprising information processing about counter-stress options in order to ascertain the most advantageous, stress-mitigating selections. A prominent form of coping with stress called Decisional Control, for example, consists of positioning oneself in a multifaceted stressing situation so as to minimize the probability of an adverse social or physical event (e.g., Averill, 1973; Lees & Neufeld, 1999; Shanahan & Neufeld, 2010; Thompson, 1981). Using Decisional Control to navigate a stressing situation implies the formation of predictive judgments in order to discern and engage the most preferred option. The predictive judgments themselves would be fed by memory and visual search operations. As cognitive transactions of this nature take place in the company of psychological stress, the impact of stress itself on their efficiency comes into play.

Psychological stress can impair the information processing required to identify the most advantageous of a situation's presenting options. In this way, stress can compromise its own resolution. In turn, there may be further consequential decline in cognitive efficiency, further compromising stress negotiation, and so on (Neufeld, 1999; Levy, Yao, McGuire, Vollick, Jetté, Shanahan, , Hay, & Neufeld, 2012).

Psychological stress also stands to improve cognitive functioning, ostensibly with resultant beneficial effects on related cognition-intensive coping. Consider, for example, the left-hand side of the Yerkes-Dodson inverted-U relation between "arousal" and performance (e.g., Gould & Weinberg, 2011; Humphreys & Revelle, 1984). A proffered mechanism of improved performance is that of attentionbandwidth narrowing (Anderson, 1990a; Easterbrook, 1959; but cf Anderson, 1990b; Neiss, 1988; 1990). As stress activation increases, so does exclusion of putatively extraneous task cues, leading to performance improvement. Following an optimal level, additional stress activation produces further attention narrowing, to the exclusion of flanking cues, some of which are task relevant, now leading to performance decline.

Finally, at least in principle, stress may leave cognitive efficiency unaffected (Neufeld, 1996). Our focus here is on performance decline, with respect to reduced accuracy and/or increased latency in transacting a relatively simple perceptual task—one that is unembellished with collateral cues.

By and large, proposals regarding how stress might affect cognitive performance have not been lacking. For the most part, however, proposed effects have not been integrated into analytical models, so as to enable precise expression of their consequences. Analytical modeling developments presented by Jim Townsend, and his coworkers and students, present themselves as highly hospitable to such analyses. The present chapter is devoted to examining selected prominent proposed stress effects, within some of those developments. Formalizing proposed stress effects, such as reduction of cognitive-workload capacity for a designated task, ushers in specific model-based tests of such effects. It also provides cognitive- and statistical-science principled measurement models for the assessment of individual differences in the proposed effects.

Further motivation for analyzing stress effects on cognition arises from the effects' possible impingement on task performance in occupational other field settings. Stress effects can be of considerable interest when it comes to human-factors ecology, cognition-related ergonomics and cognitive cybernetics. Stress effects on cognitive functioning additionally are thrown into relief arguably in such demanding contexts as those of aviation, space travel, and military actions (e.g., Davies, Matthews, Stammers & Westerman, 2000; Leiden, Laughery, Keller, French & Warwick, 2001). Successful task performance might even be viewed as a type of coping—in this case with the threat of performance failure, or inferior performance. Stress effects once again infiltrate cognition entering into coping, in this case with the threat of sub-optimal performance.

Overview.

Stochastic Modeling and Proposed Effects.

Anchoring potential stress effects in stochastic mathematical models affords the rigor, transparency and parsimony of precise derivations. Stress effects on the processes whose development is governed by probabilistic laws (Doob, 1953) can be appreciated by examining the structures of model expressions, possibly aided by computational resources, where expressions are especially complex.

Stochastic modeling relations between stress and cognitive performance to a large extent invokes parametric stochastic distributions. Parameters of such distributions often align with important stress-cognition constructs (e.g., processing capacity and its allocation to task components; intrusion of task-irrelevant operations). Such distributions also lend themselves to stochastic mixture models, whose parameter mixing distributions accommodate for example individual differences in model properties (e.g., Batchelder, 1998).

The structures and parameters of parametric models moreover cater to theoretical explorations of stress effects, disclosing potentially important consequences for performance, and available estimates of variation across individuals. Such explorations can deliver otherwise intractable insights into the substantive domain. Past forays into the integration of stress effects and those of stress-susceptibility, with parametric stochastic models, have been encouraging (Neufeld & McCarty, 1994; Neufeld, Townsend & Jette, 2007). Current applicability of Jim Townsend's parametric instantiations of his distribution-general developments point to the remarkable half-life even of the distribution-specific cases in point. Within the present topic domain, distribution-general, and distribution-specific approaches nevertheless continue to play off each other (e.g., Neufeld, et al, 2007; Townsend, Fific & Neufeld, 2007).

Layout.

Presented first is a description of representative experimental paradigms and findings. Following on are tendered explanatory mechanisms of stress effects on cognitive performance. Emphasis is on conjectured reduction in cognitive-task processing capacity, and tendency toward more serial completion of task components. Capacity reduction perhaps is the most basic of posited stress effects, and its study has been done with some of the simpler and more familiar experimental paradigms. Other suggested mechanisms of stress impact, such as change in deployment of processing capacity to task components, distraction by intrusive associations like fear of failure, or comparison to others, and premature termination of processing have been enumerated in alternate sources (e.g., Bourne & Yaroush, 2003; Davies et al, 2000; Neufeld, 1996; Neufeld & McCarty, 1994; Neufeld, et al, 2007; Staal,2004).

Stochastic modeling illustratively is undertaken on results from a study using a simple experimental paradigm, involving span of apprehension (SOA). The paradigm is administered to two groups of participants, psychometrically designated as differing in stress susceptibility. Capacity reduction is stipulated within serial and parallel stochastic model structures. Doing so introduces precise empirical testing of modeled effects, and extensions to estimation of effects at the individual-participant level.

More broadly, the presentation and developments can be viewed as using “the method of illustration” (Kuhn & Nasar, 2007). Procedures implemented in the current context arguably have more general application – to other studies of capacity, and model structure, as well as studies of other effects of stress. Illustrated via the current topic is exploitation of the potential wealth of information in extant literature – making for a sort of substantive meta-analysis (Neufeld, 2007a ;b; 2015; Novotny, 2009). Moreover, coherence of conjectured mechanisms of stress effects with results from published studies demonstrably can provide a scaffolding for testable theoretical extensions that project beyond the immediate analyses. The current application supplies a “proof of principle” regarding the substantial information on stress effects, and their individual variation, available even from very rudimentary research paradigms.

In the spirit of this volume, the extraction of rich information from modest empirical data is a testament the rigorous and pellucid Townsendian infrastructure which forms the foundation on which the current and related developments stand. Jim Townsend probably did not espy the value of his work to clinical science. Nor is it grandiose to state it may not have been predicted that beneficiaries of his achievements on the fundamentals of human cognition ultimately would include clients of science-adhering practitioners. As for longevity and proliferation, the elongated half-life, and far-reaching impact of Jim's work on clinical science-- including clinical cognitive neuroimaging -- are self-evident.

Studies of Stress Effects on Cognitive Performance

Experimental studies of this subject typically have implemented stressors in the form of aversive physical stimuli, such as loud noise. In addition, participants have been subjected to social evaluation of task performance, sometimes with instructions that performance is an indicator of social intelligence, or academic potential (e.g., Mothersill & Neufed, 1985; Sarason, 1984). Systematic variation in stress level further has been achieved by separating participants according to psychometrically identified individual differences in stress susceptibility. Using such procedures, numerous studies have reported performance deterioration, relative to less, or non-stressing variants. Experimental tasks have been wide ranging. They have included, for example, procedures tapping visual and memory search. Fewer items have been apprehended from brief visual displays by "test anxious" participants (Hamilton, 1980), and visual target detection latencies have increased among participants classified as more stressed by aversive loud noise (Neufeld & McCarty, 1994). Under the latter stimulation, memory search (scanning a memorized list of items for a target item; Sternberg, 1975) also has been slowed (Millar, 1980).

Some Conjectured Mechanisms of Stress Effects: Contextualizing the present application.

Proposed accounts of stress effects on cognitive performance have developed along several lines. Performance decline has been attributed to a reduction with stress of processing capacity (Kahneman, 1973; Schneider & Shiffrin, 1977) available to the assigned or selected cognitive task. Capacity may be diverted to contextual stimuli, necessary to aid predictability of threat-related stimuli, and covert coping activity (Cohen, 1978; Hasher & Zacks, 1979; Keinan, 1987). Environmental stressors may be salient, and thus command increased attention, especially among anxious, stress-prone individuals (e.g., Frewen, Dozois, Joanisse, Neufeld, 2008; White, Ratcliff, Vasey & McKoon, 2010). Other candidate sources of reduction in processing capacity include proprioceptive signals from autonomic activation, potentially representing information to be processed in its own right (Mandler, 1984). Like other accounts of stress effects on information processing, hypotheses surrounding capacity reduction generally have been framed in non-formal, qualitative, or occasionally quasi-formal terms (e.g., Hamilton, Bower & Frijda, 1988; Hockey, Gallard & Coles, 1986; Ouimet, Gawronski & Dozois, 2009; see also Neufeld, Townsend & Jette, 2007).

Current theories of stress-related improvement in performance have concerned allocation of capacity to task components, and second, the serial versus parallel structure of processing. Attentional capacity may be preferentially allocated to certain task aspects of the task perceived to be more important to overall performance success (e.g., spatial locations containing a designated primary task component). This tendency putatively is accentuated by stress (Broadbent, 1981; Cohen, 1978). Such non-uniformity of allocation may be decisional, or strategic (Broadbent, 1971), and may be a response to stress-induced reduction of capacity previously available to the central task element (Cohen, 1978; see also, Hockey, 1979). An attempt may be made, then, to maintain performance level by preserving or enhancing the processing of subjectively key parts of a multifaceted task.

The presence of stress has been considered by some authors to promote serial than with parallel processing. Accordingly, task requirements for transactions that proceed in sequence, rather than simultaneously, may benefit under conditions of stress. Gjerde (1983) has tendered neurophysiological mechanisms that may underlie a putative increase in prominence of serial processing. Additional lines of reasoning speak to the structure of processing in relation to stress. Deffenbacher (1994) has used a "two-mode model of attentional control", put forth by Tucker & Williamson (1984), along with a cusp-catastrophe response surface (see, e.g., Guastello, Koopmans & Pincus, 2009) depicting effects of "anxiety" and "physiological arousal" on performance. Deffenbacher's theoretical synthesis in part states that tasks involving simple perceptual intake, such as template-match visual search, are apt to be attended by a parallel processing structure, especially in the presence of reduced autonomic arousal, and relatively low organismic anxiety. On the other hand, tasks of "mental concentration" (e.g., mental arithmetic, symbolic problem solving and proof reading) are thought more likely to summon a serial structure, more so if carried out in the context of autonomic arousal and greater anxiety and "performance apprehensiveness".

Other theorists (e.g., Cohen, Evans, Stolols & Krantz, 1986) have cited evidence indicating that stress may facilitate specifically the sequential encoding of items, such as letters, for storage. Similarly, Eysenck (1976) has suggested that findings of reduced latencies for the processing of physical over semantic item attributes during stress activation can be understood in terms of a stress-induced tendency toward reduced concurrent processing of multiple word properties.

Millar (1980) studied performance on a Sternberg memory search task taking place under noise stress. The slope of the function relating reaction time to memory-set size was found to be elevated, relative to that for neutral conditions. The increased elevation was attributed to a reduction in the rate of comparing the target item to constituents of the memory set, implying reduced processing capacity.

In the quantitative developments presented below, issues of capacity reduction, and to a lesser degree those of serial-parallel processing structure, are addressed. Processing capacity and structure of the apparatus in which it operates, are two of the more prominent constructs in this field, and are shown to be accessible to modeling, its testing, and to individual-difference assessment. Stress effects on formally specified processing capacity first are examined with respect to proposed serial and parallel processing structures. The operation of capacity is stipulated within each structure, and the tenability of capacity reduction, along with that of the embedding structures themselves, are evaluated. The more plausible structure then is selected to craft a measurement model for the assessment of processing capacity at the individual-participant level.

Modeling stress-related reduction in task-wise capacity, model testing, and measurement of individual differences.

Decline in speed and/or accuracy of processing under stress has frequently been attributed to diminished “processing capacity”. Capacity reduction also has been identified with a disproportionate lowering of performance with increasing task load, when performance occurs in the presence of stressors (e.g., Finkleman & Glass, 1970). The disproportionate deterioration is deemed to be consequential to the toll taken by stress on spare capacity left to negotiate the additional load of the assigned, or central task (e.g., Fisher, 1986). Processing capacity available to withstand increased load of the designated task (e.g., expanded memory-set size, or probe-item encoding requirements of a memory-search task; or increased visual- array size, of a visual-search task) typically has been inferred directly from change in performance speed and/or accuracy as such load increases.

To elaborate, stressing stimulation has been considered by some potentially to impinge on the limited attentional-resource pool shared by a central tsk (Cohen, 1978; Fisher, 1986; Hasher & Zacks, 1979). For instance, environmental threats, and their perseverating effects, may impose their own degree of processing demands, overlapping with those of the central task. Analogous to a dual-task situation, central task performance presumably suffers if attentional resources on which it depends are drawn off by extraneous stress-related stimulation (Fisher, 1986). Moreover, reduction in available capacity is apt to be greater for individuals who are perceptually more sensitive to aversive stimulus properties (Eysenck, 1989; Williams, Watts, MacLeod & Matthews, 1988).

As processing capacity is inferred from performance speed/accuracy response parameters, with the latter themselves thought to be influenced by processing capacity, the explanatory value of the capacity construct is compromised. In addition, several properties of a processing system can adversely affect performance; not all such properties may qualify as part of the capacity construct. The present formulations distinguish model features conveying diminished capacity from other candidate sources of performance impairment. The latter include a shift to a putatively less efficient processing structure, and a capacity-affecting model parameter arguably dissociated from stress effects proper.

Capacity reduction in span of apprehension (SOA) among test-anxious individuals.

The task on which our developments focus was one that requires participants to report items from a designated location of a brief visual display. Hamilton (1980) required participants to report items from a designated location of the display (partial report procedure; Sperling, 1960). Performance was measured as the number of items processed, given the limited durations of stimulus presentation. Participants were divided into two groups based on psychometrically designated proneness to stress (Test Anxiety Scale for Children, TASC; Sarason, Davidson, Lighthall & Waite, 1958). The format of data reported by Hamilton (1980) comprised participants' means in the number of alphabetic letters processed over trials of a brief visual display. A square matrix of letters tachistoscopically was presented for .05s, preceded and followed by a blank mask. Participants were requested to report as many as possible of the letters from one of the lines or columns of a 4 x 4 matrix, according to a post-exposure indicator. Number of letters processed on each trial was estimated by multiplying the number of letters reported by the number of lines/columns in the display (i.e., 4), this estimate being the dependent variable.

Participants, aged 10 and 11, were designated as high or low anxious according to their TASC scores. Because Hamilton (1980) reported the percentage of subjects attaining each possible *SOA* mean score, as taken across the experiment's 30 trials, the overall group mean, and variance of individual means in number of letters reported, could be calculated for each group of participants. These means, and inter-subject variances, were lower for the more stress prone individuals. The study therefore was simple enough, belying potentially rich information on stress-cognition relations discoverable with an appropriate quantitative toolbox.

In the following developments, both serial and parallel processing of display items, as well as a hybrid of serial and parallel structures, are considered. In each instance, individual-participant capacity v is aligned with the rate of processing an item—that is, v is an individual's element-wise rate of processing (e.g., Townsend & Ashby, 1983). The number of display items processed by time t (.05 s.), with items being processed in serial, is represented as a Poisson process, with its associated distribution of the number of items completed by a certain time t ($0 \leq t \leq \infty$). The parallel structure is represented by a Bateman distribution, which is like the Poisson Distribution, but allows for unequal rates of processing with the successive completion of items (see e.g., McGill & Gibbon, 1965). Changes in item-completion rates in the present case are governed according to an independent parallel process with unlimited capacity (Townsend & Ashby, 1983). This model stipulates that that rate of processing applied at the individual item level v theoretically remains constant, even though items may be added to the display (although not done in this study); it remains constant as well as the display items stochastically are completed in succession. The rate of completing the next item from amongst the n items still being worked on, is nv . This structure also is known as a "pure death system, with a linear death rate" (cf. Morrison, 1979). For both the serial and parallel structures, completion times for individual items are exponentially distributed ; in the serial case, the exponential rate parameter is constant, and in the parallel case, it varies according to the number of items that continue to be processed in parallel.

Regardless of which structure is more plausible, there are apt to be non-trivial individual differences in performance. In fact, the coefficient of variation [(inter-participant standard deviation in mean SOA)/(group mean SOA)] for the less-stress-susceptible group was .356, and that for the more susceptible group was .383. By McKay's χ^2 approximation, the first value was non-significantly higher than a referent of .297, considered to indicate the possible presence of systematic differences in performance (Neufeld, Boksman, Vollick, Georte & Carter, 2010); the second value significantly exceeded the referent amount , $\chi^2_{(19)}$ = 30.15. $p < .05$. A candidate source of these differences is variation across individuals in values of performance-model parameters, over and against fixed parameter status applicable to all individuals. These differences result in over-dispersion of the performance variable (Batchelder & Riefer, 2007).

Provision is made for individual differences in the capacity parameter v, as follows. This parameter is deemed to be gamma distributed (e.g., Evans, Hastings & Peacock, 2000), with scale parameter r, and shape parameter k. The value of v varies from 0 to infinity, with mean k/r, variance k/r^2, and mode $(k\text{-}1)/r$. Gamma's shape can approximate the normal, depending on k. The gamma distribution is conjugate with the Poison and Bateman distributions, as well as with other distributions from the exponential family. Upon consideration, other candidate priors, or mixing distributions for v, such as Jeffrey uninformed (see, e.g., Berger, 1985) offer no apparent advantage to the present developments. Substantively, the parameter k, which moves the distribution of v to the right, has been identified with task-wise performer competence, and r, which moves the distribution to the left, with stress effects. These properties have been inferred from analytical considerations (Neufeld, 2007b; briefly described, later). The substantive significance of these hyper-parameters of v's mixing distribution makes for a *content-grounded* cognitive-modeling extension into the realm of parameter mixing distributions, or Bayesian priors (cf. Busemeyer & Diederich, 2010, p. 193).

The serial and parallel structures are compared for empirical fit. They are compared, as well, with respect to selective sensitivity of their model parameters to levels of stress susceptibility, as currently measured. A parameter whose substantive meaning is unrelated to an independent-variable manipulation (psychometric separation of participants) in principle should fail to express the effects of that manipulation on performance, as compared to one substantively aligned with the manipulation. As applies here, results from extensive analysis of the comparative effects of k and r on model-predicted latency distributions (Neufeld, 2007b; Neufeld & Williamson, 1996; cf. Pitt, Kim, Navarro & Myung, 2006) have been coherent with the proffered interpretation of these parameters. A summary of conjectured stress effects addressed in this chapter, their model implementations, and tests of empirical fit are presented in Table 1.

Insert Table 1 about here.

Stress-susceptibility effects on SOA; a serial-process model.

Beginning with the serial case, randomly mixing the Poisson distribution on a gamma-distributed v, produces the following probability of completing exactly j items by time t:

$$\frac{r^k\,\Gamma(k+j)\,t^j}{j!\,\Gamma(k)\,(r+t)^{k+j}}\quad, \qquad (1)$$

which interestingly also is the negative binomial for the probability of j failures before k successes, allowing $t \equiv 1\text{-}r$, and $0 < r < \infty$. The probability density function, with respect to time t, for the completion of j items, in turn is

$$\frac{r^k\,t^{j-1}\,\Gamma(k+j)}{(j-1)!\,\Gamma(k)\,(r+t)^{k+j}}\quad. \qquad (2)$$

With respect to the study's empirical data, the model-predicted group mean for the number of display items processed is kt/r where t is the display duration of .05 s. The inter-participant variance requires consideration both of within-participant variance, given v, and between-participant variance associated with individual differences in v. Their combination comprises the expected value of the variance in items processed by time t, given v, and variance in their expected value, given v (e.g., Parzen, 1962). Remembering that each participant's mean is taken across g (=30) trials, provision for both these sources of variance leads to the following predicted inter-participant variance in mean number of apprehended items, $\sigma^2_{model_{inter-participant}}$:

$$\frac{kt}{rg} + \left[\frac{(k+1)kt^2}{r^2} - \left(\frac{kt}{r} \right)^2 \right] \tag{3}$$

$$= \frac{1}{g} \left(\frac{kt(r+gt)}{r^2} \right) .$$

The observed mean, and inter-participant standard deviation in mean performance of the low-anxious participants, were 6.0 and 2.135; those for the high-anxious group were 4.88 and 1.868.

As model expressions were quite transparent, parameter values were found by equating predictions of the group means and group-wise standard deviations in individual's means, to the observed values, and solving directly. Testing of model fit used the following ANOVA-based χ^2 format (e.g., Kirk, 2013; see Snodgrass & Townsend, 1980; for clinical-science implementations, see e.g., Neufeld, et al, 2010):

$$\sum_{w=1}^{W} \frac{\left(x_{observed_w} - \mu_{model_w} \right)^2}{\sigma^2_{model_w}} . \tag{4}$$

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In the case of mean number of items, $x_{observed_w}$ is the observed mean for group *w*, μ_{model_w} is the model-predicted, or model-prescribed "population mean" for the group, and $\sigma^2_{model_w}$ is the group's model-prescribed variance in sample means (i.e., expression (3), above, divided by the group-sample size, of 20). For the individual means in apprehended items, the $x_{observed_w}$ now comprise these individual observations, μ_{model_w} is the mean for the group to which the individuals belong, and $\sigma^2_{model_w}$ consists of the group's model-prescribed population variance in these individual mean values (expression (3), above). The model-predicted, rather than observed means were used, because modeled observed variances were maximum-likelihood, rather than unbiased estimates (Neufeld, et al, 2010).

A complementing, potentially more sensitive index of fit, is the reduced sum of squares (*r.s.s.*; e.g. Wickens, 1998). The *r.s.s*. computations were applied to observed and model-predicted group means and standard deviations of individual performance means, as follows. The sum of squared deviations of model-predictions from observed values was compared to the sum of squared deviations of observed values from their mean. The latter was the grand mean, in the case of group means, and it was the average standard deviation taken across the two groups, in the case of the standard deviations. The *r.s.s*. index became the ratio of the model-prediction sum of squared deviations, to the empirical-mean sum of squared deviations (see Table 1).

The fully paramaterized mode had a value of *r* and of *k* for each stress-susceptibility group. The value of *r* for the low-susceptibility group was .0688, and *k* was 8.2602; *r* for the high-susceptibility group was .0733, and *k* was 7.1584. A perfect fit was obtained, with *r.s.s.* for both the means and standard deviations being 0. In contrast, for a base model, with a single value of *r* (.0722103), and *k* (7.94515), average *r.s.s.* was 1.0. Together, these observations suggest that the present model structure may be tenable, and that parameter values within that structure vary across stress-susceptibility groups.

A reduced model, where *k* was fixed across groups at 7.7093, and *r* was allowed to increase with stress susceptibility, from .0653075 to .07752, resulted in a $\chi^2_{(df=37)}$ of 39.92, $p \approx .34$; and the change in χ^2 with one *df*, $\Delta\chi^2_{(df=1)}$, from the base model of 3.57, $p \approx .0588$.

Note, however, that the average *r.s.s.* was close to 0, being .02. Recall that separate analyses of *r* support its candidacy as a parameter expressing effects of stress or stress-susceptibility on processing capacity.

A second reduced model fixed the parameter *r* across groups, and allowed *k* to vary. Variation in psychometrically designated stress susceptibility would not be expected to align with a change in organismic competence to apprehend brief visual displays. Based on the factor structure of the TASC (McNeil & Phillips, 1974), and previous findings on stress susceptibility (Neufeld & McCarty, 1994; Neufeld, Townsend & Jette, 2007), any reduced capacity of the stress-susceptible group would be expected to take place through an increase in the parameter *r*, over and against a reduction in the performer-competence parameter, *k*. Such selective influence on model fit across levels of susceptibility arguably speaks to validity of the model structure hosting the parameter changes.

The present reduced model again fit the data nearly as well as the fully parameterized model, with its χ^2 , $\Delta\chi^2$, and *r.s.s.* values being virtually identical to those of the previous reduced model. [2] In this way, the serial structure failed the test of selective sensitivity of its parameters to experimental manipulation.

Model over-flexibility of this nature is analogous to that of a saturated model, where each prediction is data-prescribed (e.g., relative frequencies of empirical events determine parameter values of a multinomial model). The resulting fit is perfect, but is of no explanatory value.

Stress-susceptibility effects on SOA; a parallel-process model.

Implementing the Bateman distribution, described above, with its rate parameter *v* being $\text{gamma}_{r,k}$ -distributed, the model-predicted mean number of items apprehended is (Morrison, 1979)

$$D\left[1-\left(\frac{r}{r+t}\right)^{k}\right], \tag{5}$$

where D is the display size, in this case 16. The model-predicted variance in mean number of items reported, across participants, $\sigma^2_{model_{inter-participant}}$, is

$$\frac{\left\{D\left[\left(\frac{r}{r+t}\right)^{k}-\left(\frac{r}{r+2t}\right)^{k}\right]\right\}}{g}+D^2\left(\frac{r}{r+2t}\right)^{k}-\left[D\left(\frac{r}{r+t}\right)^{k}\right]^2 . \tag{6}$$

Note that this expression has been simplified by stating the model-predicted variance in individual means of items *not* reported across the g (=30) trials (see, e.g., Morrison, 1979).

The fully parameterized model, yielding a perfect fit, rendered the following set of parameter values: r for lower and higer stress susceptibility was .46646 and .59957; k for lower and higher stress susceptibility was 4.6158 and 4.5425. The base model, with a single value of r (.535) and of k (4.683) again produced an *r.s.s.* of approximately 1.0. The parallel structure was tenable, and its parameters evidently are not constant across the stress-susceptibility groups.

A reduced model, fixing k at 4.579, and increasing r with higher stress susceptibility, from .46257 to .60464, led to an average *r.s.s.* of only .0014. Its

$\chi^2_{(df=37)}$ (whose format is described above, now adapted to the parallel case) was 40, $p \approx .29$, a change from that of the null model of 3.55, $p \approx .06$.

A reduced model constraining parameter change with stress susceptibility to k was unsuccessful in matching the change in r with respect to the empirical fit to model predictions. With r = .51083, and k under less stress susceptibility being 5.0325, decreasing to 3.4387 under higher stress susceptibility, average *r.s.s.* was .40646. Its $\chi^2_{(df=37)}$ = 41.0406, $p \approx .2843$, was not dissimilar to that of the base model, $\Delta\chi^2_{(df=1)}$ = 2. 5164, $p \approx .1127$.

Unlike the serial structure, empirical fit for the parallel structure selectively equalled that for the fully paramaterized model, with a change in *r*, but not *k*. The parallel structure therefore was supported according to the agreement of admissible parameter change with the nature of the experimental manipulation (group segregation).

Reconsidering the effectiveness of a shift in *k* across groups for the serial structure, it is possible that *SOA* performance may be affected by IQ and/or motivation (Crawford, Deary, Allan & Gustafsson, 1998; Kranzler & Jensen, 1989). If so, group differences in performance perhaps owing to inadvertent differences in IQ, could be expressed through *k*. Empirical evidence pertaining to TASC—IQ relations, however, has been equivocal at best (Bauer, 1975; Nicholls, 1977; Singh, Kumar, D'Souza & Singh, 1997). For the parallel structure, a change only in the parameter *r* was successful in fully reproducing the empirical observations. .The marginal parallel-structure result with a change in *k*, then is in keeping with the tenuous if any relation between TASC scores and performance-related mental-ability measures. Further, task salience and motivational factors, potentially incrementing *k* , if anything arguably should increase with greater fear of failure among the higher-susceptible group.

In agreement with "test-apprehension" interference with performance, as tapped by the TASC, change in *r* acting on its own effectively reduced the deviation of parallel-model predictions from observations to 0. Support for the parallel structure took the form of resistance of such reduction to change in a parameter whose sources of influence defensibly remained stable across levels of test-apprehension stress susceptibility. In this way, the parallel structure withstood the test of "over-flexibility" in the model-selection gauntlet..

Hybrid serial-parallel structure.

Each of the above models represents a mixture model, whereby the basic information-processing system (Poisson; Bateman) is mixed on its randomly-distributed processing-rate parameter. A further mixture comprises a hybrid model, whereby the above infinite, continuous mixtures themselves are implemented into a discrete finite probability mixture-- altogether making for a compound, or hierarchical mixture. In this case, the hyper-parameters r and k are constant across the stress-susceptibility groups, but the structure to which they apply can be predominantly, or exclusively, serial or parallel, depending on group membership.

Motivation for exploring this competing-model extension is as follows. It is possible that better performance for the less stress-susceptible participants is conveyed expressly by a more efficient, parallel-model architecture, over and against a serial architecture, more characteristic of stress-susceptible individuals. It also may be that for both groups, a serial structure occurs for a portion of task trails, a parallel structure occurring for the complement. In such a case, the serial structure may tend toward greater frequency among more stress-susceptible participants.

The two structures were combined by introducing a serial-structure probability $\boldsymbol{p}$ to the lower-stress group, the parallel-structure probability being its complement 1-$\boldsymbol{p}$. An analogous parameter $\boldsymbol{P}$ was assigned to the higher stress-susceptibility group. These parameters were occurred alongside a single value of r and of k spanning both stress-susceptibility levels. The possible number of free parameters again was constrained by the total of 4 available observations, comprising a mean and standard deviation for each of the 2 stress-susceptible groups.

Predictions from the hybrid model failed miserably to conform to empirical observations. For example, r and k were set as an amalgam of the 4 values of r and the 4 values of k of the fully parameterized serial and parallel models. Estimates of ***p*** and ***P*** indicated the serial structure was more prevalent for the higher-susceptibility group, ***P*** = .7586 versus ***p*** = .68749. Model predictions, however, severely missed the mark, as summarised by an *r.s.s.* value of 124.24. Similar prediction failure accompanied ***p*** being set to 0 and ***P*** being set to 1.0 (while estimating single values of *r* and *k*), thus forcing a complete change from parallel to serial structure, with higher-stress susceptibility.

Poor fit was attributable to constraining the same set of hyper-parameters, *r* and *k* to serve in a mixing distribution stochastically feeding a capacity parameter *v* simultaneously to very different processing structures. Allowing, or forcing structures to vary over levels of stress susceptibility did not compensate for the non-tenability of this constraint.

Finally, note in passing that unlike the fully parameterized models, above, the present model structure with its 4 free parameters ***p***, ***P***, *r*, and *k* did not lend itself to a perfect-fitting solution.

Isolation of stress effects on cognitive performance.

Effects of stress and stress susceptibility on cognitive performance, in the form of a disproportionate decline of performance in the company of stress, previously has been ascribed to stress-induced reduction in task-wise cognitive capacity. Impingement on capacity, in turn, has been inferred from the disproportionate performance decline itself. The circularity is obvious.

In the present application, process models of performance have been introduced. Doing so has allowed for the isolation of model properties—model structure and model parameters—potentially affected by stress levels. Stress effects have been transduced to a change in a model parameter whose increase moves a distribution of individual capacity values-- specified as the rate of constituent task transactions -- to the left. This parameter, moreover, is shown to operate within a processing system whose constituent operations proceed in parallel.

Formalization of cognitive performance and the nature of stress encroachment, however, goes beyond redressing circularity. It ushers in a quantitatively-disciplined measurement apparatus for estimating processing capacity at the individual-participant level.

Implications for individual-assessment technology.

The constructed mixture naturally ushers in participant-level measurement models, as follows. Considered first is the maximum likelihood of task-wise capacity v. For the parallel model structure, above, this estimate is available as $-\ln(1\text{-}prop)/t$, where *prop* is the sample estimate of the proportion of the display that has been apprehended during its brief presentation. Taking the mean across-trial performance of the lower stress-susceptibility group (i.e., 6.00 out of the display of 16), the maximum likelihood estimate of v is 9.4, with a standard deviation of 6.504 (see, e.g., Riefer & Batchelder, 1988), and a 95% confidence interval of approximately .579 to 25.565.

The average value of v's mixing distribution, with $k = 4.5793$ and $r = .46257$ (values for the most parsimonious, close fitting mixture) is 9.9. Its standard deviation is 4.626, and the 95% confidence interval is approximately .834 to 18.967.

With the mixing distribution of v providing a Bayesian prior, a Bayesian individualized estimate of v is available as $E(v|prop)$. Because it incorporates information from both the prior, and the performance sample, the Bayesian estimate should exceed each separate one in precision. Accordingly, $E(v|prop) = 9.622$ (Bayesian shrinkage being expressed in movement from the maximum likelihood estimate toward that of the prior). The standard deviation of v now is 2.976, with a 95% confidence interval of approximately 3.79 to 15.455. This interval is less than half that of the prior, and .6433 that based on the empirical data alone.

Extensions.

Moments.

The SOA performance, above, and its translation into an infinite continuous mixture model, can be used to project the moments of latencies to process the entire visual display of alphabetic items. The *n*th moment about the origin for the parallel structure is found to be:

$$\sum_{i=1}^{D} \frac{(-1)^{i+1}\binom{D}{i} r^n\, n!\ \Gamma(k-n)}{\Gamma(k)\, i^n}\ . \qquad (7)$$

With the value of k being 4.5793, and the lower-stress-susceptibility group's value of r being .46257, its mean latency is projected to be .4369 s, and its variance, .1107 s^2. For the higher-susceptibility group, with r increasing to .60464, the projected mean latency becomes .571096 s, with a variance of .18919 s^2. Note that these values may be underestimates, because the duration of processing in the SOA task, from which parameters were estimated, may have been longer with trial termination by a blank mask, than it would have been with a pattern mask.

It is apparent from Equation (7) that $E(T^n)_{r,k}$ is finite iff $k>n$. This relation has been shown more elaborately and expanded upon in Neufeld (2007b). If $k = n$, the integral for the nth moment does not converge; equivalently, there is a discontinuity of the nth derivative of the moment-generating-function, where its parameter of transform $\theta = 0$. If the nth-order moment of the distribution is note finite, neither are those for orders exceeding n (e.g., Harris, 1966). The substantive interpretation of this result is that k is below the task-wise competence value that would prevent a critical corpus of extremely long, or incomplete trials, sending the nth moment to infinity. A value for k of 2 or less indicates performance breakdown in terms of an infinite latency variance for the processing entity to which k refers. A value for k of 1 or less indicates more serious breakdown, in terms an infinite latency mean. Estimates of k from the current analyses invariably exceeded 3, indicating finite means and variances. Observe that the processing entity to which k presently applies is a class of stress-prone individuals. Bayesian extensions to the single individual as the processing unit have been presented in Neufeld (2007b).

The interpretation of k as a task-related performer-competence parameter previously has been developed from an analytical perspective ("analytical construct validity" supporting parameter interpretation; Neufeld, 2007b). The current analysis exploiting secondary empirical data adds to the analytical support for this inference. Here, the parameter k was dissociable from model structure, and from an additional parameter, which nevertheless like k could affect the distribution of individual capacity values.

Systems Factorial Technology Cognitive-Capacity-Workload Analysis..

The stress-related differences in distributions of individual capacity values, above, are manifest on a final common pathway provided by Townsend and co-workers' Systems Factorial Technology. The capacity-workload index (CI) is the hazard function $f(t')/S(t')$, integrated form $t' = 0$ to $t' = t$, $\int_0^t \frac{f(t')}{S(t')}\,\mathrm{d}t'$, where $f(t')$ is the processing-latency distribution density function, and $S(t)$ is the distribution's survivor function. This integral can be estimated as $-\ln(S(t))$ (Townsend & Nozawa, 1995; Wenger & Townsend, 2000). Focusing on the processing of an individual item of the SOA-paradigm display, the estimate of $S(t)$ consists of the proportion of items not processed by $t = .05$. Taking as a less stress-susceptible prototype the mean performance value of that group, the item-level value of CI is .47, and the value for the more susceptible group is .36.

Qantified in this way, and then converted to the Capacity Ratio (CR) , the cognitive workload capacity in the case of higher stress susceptibility is approximately 3/4 (i.e., .774) that of the less susceptible group. It is no stretch to imagine how such differences could ramify into more macroscopic products of more complex cognitive systems.

Such a more complex system of course is that handling the full array of items in the SOA display. As prescribed by the parallel-processing mixture model, $S(t) = -\sum_{i=1}^{n}(-1)^{j}\binom{D}{i}\left(\frac{r}{it+r}\right)^{k}$.

Using the selected reduced model, above, and inserting parameter values of the less and more susceptible groups (k = 4.579 for both groups; r = .46257 for the less-susceptible group, and r = .60464 for the more susceptible group), the ratio of less- and more-susceptible CI values, CR, becomes 10.7533, substantially higher than the element-wise value of 1.3, above. Although the difference in the distribution-function (the probability of apprehending the entire SOA array) $F(t)$ is trivial at t = .05, its model-predicted value becomes less so at higher values of t. For example, at t = .38046, the difference peaks at .62085-.44398 = .17687. Early values of CR therefore may be lead indicators of later, more noteworthy differences in $F(t)$. All in all, the consequences of diminished item-wise capacity for multi-item processing, illustrated here, may be indicative of consequences for increasingly complex tasks in which SOA itself participates.

Concluding Comments

The present developments have elevated conjectured stress effects on cognitive capacity out of the realm of tautology and circular reasoning, by assimilating them into a formal theoretical infrastructure (Braithwaite, 1968; Flanagan, 1991). Doing so has enabled predictions that are isolable from those of other infrastructure properties. And the infrastructure's mixture-model composition has rendered a defensible tack to individual-difference measurement of the target construct.

Along the way, instantiations of parallel and serial processing have been distinguished according to an index adapted to the present study-- selective sensitivity of empirical model fit to parameter change, vis a vis model over-flexibility[3]. Evident is the potential informational added-value that comes from drawing out substantive inferences from existing data, specifically through the lens of analytical modeling (for additional applied-setting examples, see Neufeld, 2015; Shanahan, Townsend & Neufeld, 2015). Such discernment of parallel versus serial architectures obviously is propelled by Jim Townsend's exquisite offerings on the topic. Discernment in this case occurs even to the re-analysis of very rudimentary data obtained from a very basic experimental paradigm.

Quantitative formalization illustratively has lent itself to integration with published data summaries from a representative study of stress effects. As in the present illustration, such summaries most often have not been constructed with formal-model development and testing in mind. Instead, observations have been subjected to generic data analyses (e.g., ANOVA), accompanied by generic-analysis data- summary formats. For example, measures of dispersion have been restricted to standard deviations across participants, within groups. More model-hospitable formats would consist of moments of inter-trial, within-participant distributions of performance values; or bins of performance proportions falling into successive intervals of performance values (e.g., interval-binned response latencies). By taking up the challenge of tailoring model predictions and testing, to the format of data presentation that the literature has dealt, substantial model evaluation in principle can be released from extant reports -- including that from older, even classical studies (as cogently exemplified in Townsend, 1984).

The current developments illustrate the potential of selective application of contemporary analytical tools for disclosing otherwise untapped information. Such methodology comprises essentially an analytical toolbox for the study of stress effects on cognitive performance. The present application has been on the specific topic of processing capacity among psychometrically identified stress-susceptible individuals. Similar applications, however, are available for addressing stress effects on formally-specified capacity instead where increased environmental stress has occurred (e.g., experimentally induced intense ambient noise; e.g., Weinstein, 1974), or with a combination of stressors and systematic differences in stress susceptibility (e.g., Neufeld, & McCarty, 1994; Neufeld, et al, 2007). Such a substantive meta-analysis arguably also can be productive in investigating other stress effects on cognitive performance, and beyond.

Proposed stress effects seemingly poised for such investigation include, for example: a), stress-induced reallocation of processing resources to task components (e.g., locations of a visual array), possibly in the service of preserving performance integrity (e.g., Broadbent, 1971; 1981; Hockey, 1970a; 1970b); b), the Yerkes-Dodson effect, entailing optimal levels of stress activation, and their downward shift with increasing task load (Hamilton, Hockey & Quinn, 1972; Humphreys & Revelle, 1984); and, c), effects of task-intrusive, noise associations (e.g., Fisher, 1986; Hamilton, 1980; Sarason, 1984). Apparently available is the economical tapping of otherwise dormant information, residing with the treasure trove of results emanating from the not-inconsiderable investment in the empirical research enterprise devoted to this topic.

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List of Footnotes.

1. For an overview of definitions of psychological stress, with an emphasis on one tapping Townsend & Ashby's (e.g., 1983) quantification of cognitive-work transacted per unit time, see Neufeld (1990).
2. Note that the Poisson distribution allows for 0 to an infinite number of events. The maximum possible in the present SOA task was 16. Separate analyses, however, indicted that for the present parameter values, the probability of 17 or more completions was negligible, being approximately .005. Additional analyses of *g* statistics (skewness and kurtosis) for the present serial and parallel model distributions, indicated approximation of normality, assumed by the χ^2 statistics, there being a slight positive bias in the case of the serial model, and a slight negative bias in the case of the parallel model. Finally, not surprisingly comparative fit by *r.s.s.* agreed with that of the residual sum-of-squares version of the Bayesian Information Criterion (see also Spielgelhalter, Best, Carlin & van der Linde, 2002).
3. For a clinical-science oriented discussion of selective sensitivity of parameter change to experimental manipulations, as related to construct validity of parameter interpretation, see Neufeld, (2015),

Table 1. Summary of Hypothesized Stress Effects on Cognition, their Model Expression, Tests of Fit, and Results.

Hypothesized Effects	Model Expression	Tests of Empirical Fit Throughout	Results
Reduction in Processing Capacity for Addressed Task	Change in parameter *r* and/or *k*, which govern the distribution of individual participants' rates *v* of transacting task elements; *r* expresses stress (susceptibility) effects, moving *v*'s distribution downward; *k* expresses performer task-competence, moving *v*'s distribution upward.	ANOVA-based χ^2, whose essential format is $\frac{(x_{obs} - \mu_{model\ predicted})^2}{\sigma^2_{x;\ model\ predicted}}$. Reduced sum of squares (*rss*), whose essential format is $\frac{(x_{obs} - \mu_{model\ predicted})^2}{(x_{obs} - x_{Grand\ Mean_x})^2}$.	Near perfect fit only with change in *r*, for the parallel model architecture; near perfect fit with change in either *r* or *k* for the serial architecture, implying model over-flexibility.
Increased engagement in serial processing of task elements.	Elevation in ***p***, a discrete probability mixing parameter expressing the probability of engaging in serial processing.; available capacity is implemented into a serial structure with probability ***p***, and into a parallel structure with probability 1- ***p***. Selective sensitivity of empirical fit to a capacity-affecting parameter aligned with experimental manipulations (*r*, veridical with experimental group formation, over and against *k*, above).		Unacceptable empirical fit, whether ***p*** is set to 1.0 at higher stress susceptibility and 0.0 at lower susceptibility, or is allowed to vary across groups; change in serial processing is not supported according to this result, nor that of parameter-wise selective sensitivity. **Overall**, empirical support is obtained for capacity reduction, within a parallel processing architecture.