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Mathematical Modeling of Stress Management via Decisional Control

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Graduate Program in Psychology
A thesis submitted in partial fulfillment of the requirements for the degree in Doctor of Philosophy
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MATHEMATICAL MODELING OF
STRESS MANAGEMENT VIA DECISIONAL CONTROL

(Thesis format: Integrated Article)

by

Matthew Jacques Shanahan

Graduate Program in Psychology

A thesis submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy

The School of Graduate and Postdoctoral Studies
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Abstract

Engaging the environment through reason, humankind evaluates information, compares it to a standard of desirability, and selects the best option available. Stress is theorized to arise from the perception of survival-related demands on an organism. Cognitive efforts are no mere intellectual exercise when ontologically backed by survival-relevant reward or punishment. This dissertation examines the stressful impact, and countervailing peaceful impact, of environmental demands on cognitive efforts and of successful cognitive efforts on a person's day-to-day environment, through mathematical modeling of 'decisional control'. A modeling approach to clinical considerations is introduced in the first paper, "Clinical Mathematical Psychology". A general exposition is made of the need for, and value of, mathematical modeling in examining psychological questions wherein complex relations between quantities are expected and observed. Subsequently, two documents are presented that outline an analytical and a computational basis, respectively, for assessing threat and its potential reduction. These two studies are followed by two empirical studies that instantiate the properties of the decisional control model, and examine the relation of stress and cognition within the context of psychometric, psychophysiological, and cognition-based dependent measures. Confirming the central hypothesis, results support the validity and reliability of best-option availability $Pr(t_1)$ as an index of cumulative situational threat $E(t)$. Strong empirical support also emerges for disproportional obstruction of control by 'uncertainty', a lack of both information and control, compared to less obstruction of control by 'no-choice', a simple lack of control. Empirical evidence suggests this effect extends beyond reduction in control to an increase in cognitive efforts when even control is not present. This highlights an existing feature of the decisional control model, Outcome Set Size, an index of efforts at cognitive evaluation of potential encounters regardless of control availability. In addition to these findings, the precise specification of model expectancies and consequent experimental design, refinement of research tools, and proposal of an integrative formula linking empirical and theoretical results are unique contributions.

Keywords

Stress and coping, mathematical modeling, decisional control, threat reduction, threat index.

Co-Authorship Statement

The encyclopedia entry on “clinical mathematical psychology” is the collaboration of Matthew Shanahan, Dr. James Townsend, and Dr. R.W.J. Neufeld.

The section entitled “Toward a Comprehensive Model of Coping with Stress through Decisional Control: Exploiting Mixture-Model Properties of a Game-Theoretic Formulation” was a collaboration of Dr. R.W.J. Neufeld with Matthew Shanahan, together with valuable input from Peter Nguyen. Matthew Shanahan is listed as first author for his initiatives collecting the empirical data relevant to this work, extensive discussions with Dr. Neufeld about the Decisional Control model, his development of a full range of closed-form single-formula solutions across i values, and presentation of his work and approach in a paper given at the Society for Mathematical Psychology annual conference (Shanahan, Nguyen, & Neufeld, 2012). Dr. R.W.J. Neufeld’s work on this paper was substantial, especially in the founding mathematical structure. Authorship order was established by mutual agreement.

The section entitled “Information Processing for Threat-Reduction in Decisional Control Scenarios” was produced from a study designed by Dr. R.W.J. Neufeld and implemented by Ryan Y. Hong. Matthew Shanahan was directly involved with data collection and did the data analysis. Establishment of new metrics such as the maximizing-satisficing-simplifying continuum is Mr. Shanahan’s own work (Shanahan, Pawluk, Hong & Neufeld, 2012). Mr. Hong contributed the coding of psychometric data, and the initial coding of psychophysiological data. Elizabeth Pawluk made a substantial contribution with the preference paradigm work as her honours thesis. Multiple posters from this data set have been presented (Pawluk, Shanahan, Hong, & Neufeld, 2008; Shanahan, Hong, Pawluk, & Neufeld, 2008).

The last section and second empirical study was Matthew Shanahan’s own dissertation proposal and his own work. Dr. R.W.J. Neufeld was a significant contributor in an advisory role, and Peter Nguyen exhibited exceptional prowess in the technical programming of data collection platforms, under Mr. Shanahan’s direct supervision. Mr. Nguyen’s level of appreciation for the material and suggestions for implementation of the theoretical and experimental constructs involved in this research warranted his inclusion as a co-author.

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1 Clinical Mathematical Psychology

1.1 Introduction to the First Component Document

The first paper in this dissertation research initiative is an introduction to mathematical modeling of clinical phenomena generally. This is a nascent field. As described in the encyclopedia entry, the published format for the paper below, areas such as anxiety, neurological functioning, and psychometric testing provide just a few of many promising avenues for the application of mathematical modeling techniques in a clinical psychology context. The article inserted below first appeared in the Wiley-Blackwell Encyclopedia of Clinical Psychology (Shanahan, Townsend, & Neufeld, 2015), edited by Scott O. Lilienfeld and Robin L. Cautin.

Following the article pages (pasted as images within this document), a comment on seven aspects of direct application within the rest of the dissertation of discussed techniques, approaches and features of Clinical Mathematical Psychology are listed to end Chapter 1.

1.2 First Document: “Clinical Mathematical Psychology”

The encyclopedia article proper is presented on the 10 following pages in image format, drawn from the electronic reprints from Wiley-Blackwell.

Clinical Mathematical Psychology

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Clinical mathematical psychology uses analytical (formula) derivations to describe behavioral, cognitive behavioral, or psychophysiological abnormalities associated with clinical disorders. The quality of being “analytical” differentiates mathematical modeling from statistical modeling, and computational modeling, or computer simulation. An analytical approach involves specifying the operation of the component variables in algebraic terms within formula structures representing the processes at work. Among the most valuable results of mathematical (analytical) modeling is the capacity for precise prediction of expected empirical response properties.

Examples of predictable empirical data properties include the categories into which responses fall (e.g., correct, incorrect; stated judgments, or choice selections), response latency, and intensity or expressed confidence in one’s registered response. A particular focus has been the measurement of *symptom-significant cognitive functioning*: cognitive activity that directly relates to pathological symptoms. These characteristic deviations in cognitive functioning are measured with approaches known as “cognitive psychometrics,” “cognitive modeling,” and “quantitative clinical cognitive science and assessment.”

Methods, Approaches, and Matters of Study

Essential parts of a psychological mathematical model typically encompass the explanatory

parameters (theoretical variables) it invokes, and its structure, or organization of the parameters, in terms of their functioning in the proposed theoretical response-generating process. As such, the development and application of a clinical mathematical model is typically done to fit the particular dynamics of a particular disorder, even a particular symptom or behavior proper to a given disorder. The model is usually “custom-built,” as it were.

On the other hand, much of psychological research makes use of analytical developments with an assumed normal (Gaussian, or bell curve) distribution when it comes to data analysis. Common Fisherian and Pearsonian statistical methods, and their contemporary extensions, have been developed through mathematical formulae using an assumed structure of the data. These approaches were developed in the early twentieth century, when the assumption of well-charted distributions facilitated the strength of statistical inference. Clinical mathematical psychology tends to select or develop relevant distributions that suit the phenomenon under study more closely.

An important feature of mathematical modeling is that it extends analytical developments from the data analysis enterprise out of reliance on verbal descriptions and into the realm of theoretical reasoning. The verbal theorizing combined with analytically developed statistical methods (e.g., analysis of variance, hierarchical linear modeling, chi-square) used in much of psychology research represents a “mixed deductive scientific system.” In such a system, the research question of interest is highly developed in verbal form in both the introduction and hypothesis statement. The mathematical test of the research question is often left to a stock method from a fairly short list of established, understood techniques. In contrast, the extension of mathematical formulations to theory and hypothesis generation makes for a “pure deductive scientific system.”

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This kind of scientific system is characteristic of more established disciplines such as physics. The fundamental feature of a “pure deductive scientific system” is that its specification, testing, measurement, and vindication or falsification are conducted in a uniform language with unambiguous terms and clearly defined operations. Mathematical specification of research questions allows for this continuity of precise expression.

Clinical issues potentially subjected to mathematical modeling can range from very small-scale to very large-scale topics. At the level of an individual mind or brain, the study of cognitive functioning in clinical samples applies the rich body of information and measurement technology from the field of mathematical cognitive science to the analysis of cognitive abnormalities. At an interpersonal level, other avenues of modeling can take the form of, for example, quantitatively expressing clinically significant properties of continuous reciprocal influences between interacting parties, such as therapist–client interchange in a psychotherapeutic setting. At an even broader level, sources of vulnerability to stress and exacerbation of symptoms may be studied across a multiplicity of life settings with mathematical modeling approaches.

Clinical mathematical psychology generally implements stochastic rather than deterministic models. Stochastic models build a predictable amount of random variation into a predictive model. Models in hard sciences include this kind of variation routinely, where individual events are impossible to predict, but overall patterns are reliably described (e.g. weather patterns, molecular motion in a fluid). Doob (1953) has described a stochastic model as a “mathematical abstraction of an empirical process, whose development is governed by probabilistic laws” (page v). The stochastic aspect of model structure simulates naturally occurring random variation so as to expand deterministic model predictions, resulting in a distribution of empirical response properties (e.g., response latencies) over successive observations.

Statistical modeling concerns itself with theory of data structure for purposes of partitioning and analysis, and its mathematical foundations are not dependent on the research context. That is, the subject matter under scrutiny does not typically affect the analysis technique selected, beyond the selection of a well-known statistical test that suits the research design, rather than the research topic per se. Because hypotheses to which it is applied, by and large are nonformal (e.g., conjectured paths of influence in structure equation modeling, or moderation–mediation analysis), statistical modeling is part of a mixed deductive scientific system (a combination of verbal description coupled with a standard test of significance). As with any statistical analysis, focus is on treatment of the presenting empirical data. In contrast, the focus in mathematical modeling is on theoretical mechanisms held as responsible for bringing the data about in a direct fashion.

Computational models may be quite close to the procedures in analytic modeling but tend to emphasize incorporation of major assumptions into computer algorithms or Monte-Carlo software rather than through invention of explicit equations and the use of the latter in theorem and prediction development. Thus, in the case of computational modeling, specific rules of activation among its network of theoretical units (analogous, for example, to neurons, or neuronal modules; “neurodes”), are typically implemented through specific computer syntax and code. A network design and certain elements of its activation algorithm may correspond with selected properties of a mathematical model, such as its structure and parameters. Mathematical and computational models moreover may be mutually informative as to the mechanisms at play in a particular clinical process, or set of processes (Marr, 1982). The construction of the unit network, the strength of unit connections, and the unit-activation algorithm, nevertheless are not by and large themselves products specifically of mathematical derivations, or theorem-proof developments. It might be said

that though many such models can be crafted to generate predictive efficacy, as noted above, they are not explicitly mathematical in that they are typically constructed with “black box,” algorithm-based techniques rather than being designed with interpretable components by a human mind.

Procedurally, much of the work involved in clinical mathematical psychology resembles the method of titration in chemistry, where a reagent is introduced in careful measure to a substance to ascertain its composition. That is, many small increments or decrements must be made to the particular balance of the modeled quantities before the clinical model begins to reliably demonstrate the modeled behavior or cognitive phenomenon. The overall program involves theory building and theory correction in a dynamic interplay of modeling, clinical observation, and experimentation. Defensible models of normal functioning are modified to accommodate deviations occurring with psychopathology. Inferences are drawn from the titrated model: parts of the model that survive intact are taken to signify faculties that are spared; conversely, parts that are perturbed are triaged as signifying disorder-affected faculties.

As an example of clinical mathematical psychology applied to the study of schizophrenia-related cognitive deficits, the number of constituent cognitive operations or “subprocesses” has been shown to be involved in elongated encoding of presenting stimulation into a cognitive format facilitating further operations (e.g., in cognitively preparing and transforming a presented item for purposes of ascertaining its presence/absence among a set of earlier memorized items). Beyond the usual number of features encoded from the presented item (e.g., curves, lines, and intersections of an alphanumeric item), the individual with schizophrenia can spend an excessive amount of time tangentially transforming the presented stimulus. Increasing the number of subprocesses beyond a certain threshold in computer-assisted model simulations allows the model-generated data to closely approximate the response times obtained from

actual clinical participants. As such, the aspect of excess subprocessing is vindicated as an effective model of cognitive processing for this population.

To elaborate slightly, selected stochastic models addressing this deviation express mean process latency simply as the quantity k/v . Here, k is the number of constituent operations of the encoding process, and v is the rate of subprocess completion per unit time (“subprocess workload capacity”). Fitting predictions to schizophrenia data has occurred with elevation in k , but not a decrement in v (e.g., Neufeld, Boksmann, Vollick, George & Carter, 2010).

Typically, it is parameter values, rather than model structure that need to be changed. In some cases, however, the architecture of the modeled cognitive behavioral performance mechanism itself must be modified, in order to accommodate observed performance deviations. The technique of theory building and adjustment aligns with the scientific strategy called “abductive reasoning,” whereby existing (mathematical) theory explanatorily is retrofitted to obtained data.

Prominent issues in clinical science and assessment, notably from the cognitive behavioral domain, surround the following: cognitive workload capacity, efficiency of capacity deployment, the presence and nature of stages of processing, serial versus parallel transaction of process operations, and so-called automatic versus controlled (effortful) processing. Some of these have been addressed by existing research, or are addressable via clinical mathematical psychology approaches. Symptom-significant deviations in clinical populations (cognitive patterns likely contributing to the pathology in question) can be approached through established methods for measuring information processing, decision and choice, memory processes, concept learning, perceptual organization, and psychological stress and coping.

Contemporary developments in mathematical psychology, that also have found a home in clinical science and assessment, have provided for parameter-free, distribution-general model

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composition and empirical process diagnostics (e.g., Townsend & Nozawa, 1995; Townsend & Wenger, 2004). These theoretical formulations emanate from mathematical axioms that are universal (“distribution-free”) rather than based on an assumption of specific distributions such as the normal (Gaussian distribution). There exists associated measurement technology (known as Systems Factorial Technology) that discerns fundamental elements of cognition (e.g., serial versus alternate parallel-processing architectures of a hypothesized cognitive system, and its cognitive workload capacity).

Such developments are a unique contribution to the broader field of mathematical modeling, and their general robustness is an especially welcome feature in applied settings. Moreover in the field of psychology, they epitomize the ideal extolled by Meehl (1978), that theory testing, including the measures it uses, should emanate from the theory itself, again as seen in older scientific disciplines. In the science of particle physics, for example, the theory-driven prediction of the Higgs boson was so well supported from a foundation of mathematical inference that it justified massive resource investment in the Large Hadron Collider at CERN, Switzerland. Effective mathematical psychology theory should be able to generate novel, significant predictions and permit relevant hypotheses to be specified accurately and tested with precision.

Contributions of Informational Added Value

A presenting epistemic strategy or measurement technology will usually “carry its own credentials,” vindicating itself based on the informational “added value” it conveys. Such a payload delivered by clinical mathematical psychology is multifaceted. It includes construct-representation construct validity, the disentangling of processes conflated in generic data analysis, explanation and unification of seemingly disparate empirical observations,

and accessing otherwise intractable, or nonaddressable sources of clinical disturbance.

Construct-representation construct validity represents support for the interpretation of a measure in terms of the degree to which it incorporates mechanisms that are theoretically meaningful in their own right (Embretson, 1983). The theoretical infrastructure in mathematical modeling springs from the very subject matter under study. Analytical formulae of mathematical models have “working parts” that are in themselves substantively meaningful. In this way, construct representation is built into measures to which the modeling gives rise.

Mathematical theory, and the measurement methods it spawns, can be used to refine the treatment of research data so as to uniquely distinguish the operation of cognitive behavioral performance mechanisms among clinical groups. To illustrate, Riefer, Knapp, Batchelder, Bamber, and Manifold (2002) studied recall memory performance among individuals with schizophrenia and controls. The design was a “correlational experiment” whereby the differing groups are examined under varying conditions of theoretical interest. The conditions in this case were sequential trials of a recall paradigm, each consisting of an item-study phase, followed by a recall-test phase. Of considerable interest was the differential progression of performance over the successive trials.

Analysis of variance conducted on sheer proportions of items recalled nevertheless failed to yield a significant groups-by-trials interaction. Ordinarily, such nonfruitful traditional analyses would end with the study being “dumped.” However, careful mathematical modeling revealed important differences between the groups. In-depth analysis of storage and retrieval processes through a mathematically disciplined model of performance (known as multinomial processing tree modeling) exposed the epiphenomenal nature of the generic analysis. There was apparently an intrinsic offsetting whereby two existing effects “cancel out.” This pattern could only be

discerned, however, by the authors' application of mathematical modeling.

The use of model-driven measurement and statistical testing (part of what Riefer and colleagues term "cognitive psychometrics") revealed that the schizophrenia participants showed less improvement in storage accuracy specifically over the last three of the six study-retrieval trials. Contra this deficit, their improvement in storage accuracy actually exceeded that of controls during trials 2 and 3. Analysis of a model parameter distinguishing rate of improvement in retrieval accuracy, as set against the trial 1 baseline, showed a significantly slower rate throughout. The model-identified initial strength of storage accuracy evidently diluted later deficits, as well as those of a lower retrieval-improvement rate, to render superficially parallel the between-groups changes seen in the analysis of raw proportions of items recalled. As such, mathematical modeling suggested a more fine-grained re-examination of the data based on component processes, allowing the discrimination between a target clinical group and a control group that would have been, for all intents and purposes, invisible.

Accurately identified profiles in process strengths and weaknesses in principle can contribute to the navigation of clinical intervention strategies. They also can furnish important information about the "functional" side of functional neuroimaging measurement obtained during memory task performance.

As occurs in other applied mathematical sciences, informational added value, as bestowed by clinical mathematical psychology, can explain and unify enigmatically disparate empirical findings. Such unification can be illustrated with reference to observations on sensitivity to threat-valenced stimulation among anxiety-prone individuals.

Greater attention to threatening stimulus content (e.g., words such as "suffering" or "loss") among higher anxiety-prone (HA) in contrast to lower anxiety-prone (LA) individuals has been found across multiple experimental paradigms such as the Stroop

task, dichotic-listening tasks, and the dot-probe task. In the latter, HA individuals detect the probe more readily when in the vicinity of a threatening versus neutral visual stimulus.

The consistency of significant HA-LA group differences, however, has generally been tied to presentation of threat items *alongside* non-threat items. Such differences disappear when threat and non-threat items are present *singly*. Statistical significance of the HA-LA by threat-non-threat item interaction (significant group-item second-order difference, or, two-way interaction) is by and large restricted to conditions of co-occurrence of the two types of stimuli. Such findings have given rise to relatively complex conjectures emphasizing competition between the two types of stimuli and associated "cognitive control operations." Differences between HA and LA groups have been attributed, for example, to inequalities in cognitive tagging of threat items, or to HA participant deficit in threat-item disengagement. Difficulties in registering significant second-order differences with single-item presentations has led to questioning the potential importance, or even existence, of HA individuals' elevated threat-stimulus engagement.

The resolution of this research conundrum is that greater threat-stimulus sensitivity arguably exists among HA individuals, but this may be more strongly drawn out with the co-presence of non-threat stimuli—for reasons that are relatively straightforward. The cognitive apparatus transacting the processing task stands to be one of limited attentional resources, in this case meaning that these resources are spread between threat and non-threat items, when co-present. Items presented together furthermore arguably are processed in parallel (concurrently) among both HA and LA participants. With relatively less salience of the threat item, a greater, and possibly equalizing amount of LA participants' attentional capacity theoretically is consumed by the non-threat item, reducing the between-item difference in processing latency. In contrast, the inter-item difference would be larger for

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the HA participants, if the pre-potent salience of the threat item made for increased resistance to the non-threat item's encroachment on processing capacity.

This proposition lends itself to the following simple numerical illustration. Brought into play is a defensible processing apparatus, called an independent parallel, limited-capacity (IPLC) processing system, with exponentially distributed item-completion times. Its technical specifics notwithstanding, the workings of this system make for straightforward inferences regarding the present issue. Let the visual information-processing resources of such a system (its cognitive workload capacity) be expressed as a value of 10 arbitrary units (corresponding to the *rate* at which task elements are processed, per unit time), for both HA and LA participants. During a dot-probe task (above; particularly prominent in the present research domain), the solo presentation of a threat item fully engages the system resources of an HA participant, and possibly 90% thereof in the case of an LA participant. By the workings of this model, the mean processing latency of HA individuals is $1/10$ and that for LA individuals is $1/9$, for a difference of $-.0111$ (note that latency varies inversely with capacity, expressed as a processing-rate parameter). The solo presentation of the non-threat item, on the other hand, putatively engages 50% of the system's resources for both participants, which by the model translates into $1/5$ for both individuals, now making for a zero difference. By the IPLC model, the second-order difference in mean latency (or inequality of the differences in the means)—this being targeted in the above studies—then is $(1/10 - 1/9) - (1/5 - 1/5) = -.0111$.

For the simultaneous-item condition, 80% of the HA individual's system processing resources hypothetically remain with the threat-item location, but the LA individual's resources now stand to be evenly divided between the threat and non-threat items. By similar reasoning to the above, and retaining a capacity limitation of 10 arbitrary units, the second-order difference becomes

$(1/8 - 1/5) - (1/2 - 1/5) = -.375$. Statistical power obviously will increase with the effect size accompanying this larger second-order difference.

These developments exemplify clinical mathematical psychology's potential to explain and unite seemingly discordant sets of observations. Potential sources of discrepancy are uncovered, and disparate findings are synthesized by a common underlying process.

In addition to generating new measures, experimental paradigms, and formal-theoretical explanations, clinical mathematical psychology increasingly has been used to enrich the informational yield from tasks already routinely used in clinical science and assessment. A type of dynamical mathematical modeling, known as Expectancy Valence Learning, and its variants have been used to dissect and specify sources of performance deviation on tests such as the Wisconsin card sorting test, the Iowa gambling task, and the go/no-go task. Performance abnormalities are pinpointed to sources that are motivational (differential sensitivity to positive versus negative feedback to individual decisions), learning-related (relative influence of recent versus more remote choice outcomes), and response-related (entrenchment of responding in acquired information, versus impulsive dislodgement therefrom).

In some areas of investigation, the acquisition of clinically important information may be untenable apart from mathematical modeling. It has been suggested that analogous to selected methods in biochemistry, where a compound is considered to be understood if successfully synthesized, some aspects of psychopathology are grasped if reproduced experimentally among nonclinical samples. Certain proposed agents of performance decline, however, may defy experimental manipulation of independent variables as the sole means of study. Such may occur for ethical reasons, because of the intensity of experimental manipulations required, or because the theoretically tendered agent may elude mimicking through experimental induction (e.g., organismic endogenous

stress susceptibility put forth as producing task-impeding intrusive associations, or siphoning off cognitive workload capacity).

The direction taken by clinical mathematical psychology instead is one of introducing the suspected agent into model composition, and examining for increased conformity of predictions to deviations occurring with psychopathology. Additionally, a considerable economy of data-harvesting resources can be realized with well-designed modeling approaches. Moreover, some large-scale patterns may only be revealed in extensive simulation runs of well-tested models, where empirical data gathering would be prohibitive or impossible.

Clinical Mathematical Psychology and Clinical Neuroimaging

Clinical mathematical psychology can provide vital information on the functional aspects of clinical functional neuroimaging (functional magnetic resonance imaging, magnetic resonance spectroscopy, electroencephalography, and electro-magnetoencephalography). It can do so through stipulating precisely the cognitive events taking place during cognitive neuroimaging trials. Symptom significance is associated with monitored neurocircuitry by applying models of neuroimaged cognitive activities that intersect with symptomatology (e.g., the quantitative interlacing of formally modeled stimulus-encoding deficit in schizophrenia, with thought-content disorder; Neufeld et al., 2010).

A frequently used method of neuroimaging called event-related neuroimaging is an important method of neuroimaging. In this approach, the specific cognitive functions that are instigated by experimental manipulations of a cognitive performance paradigm are studied. Estimating the time course of such functions within a cognitive performance trial demands a tenable mathematical model of their stochastic time trajectory. Imaging signals which correspond to estimated epochs of a symptom-relevant process (e.g., encoding

a presented item, for purposes of further treatment, such as comparing it for a match to other items held in “working memory”) command special attention. Clinical mathematical modeling can specify such epochs. In doing so, it can supply “times of measurement interest” that complement “brain regions of interest,” thus rounding out the navigation of space–time coordinates of functional neuroimaging measurement (mathematical and neuroimaging specifics are presented in Neufeld et al., 2010).

Using modeled time periods of interest for measurement, symptom-relevant functions can be analysed close together with other functions to which they relate. For example, item encoding remains conjoined with, say, scanning for the item in a memory-held item-set, and possibly other processes, for which the encoding process exists. Retaining the integrity of the experimental context in which the targeted cognitive process operates preserves its functioning in situ, or its “ecological validity” as one component process among many required. As a result, ecological validity of findings may be enhanced, over and against those obtained by deconstructing the performance apparatus through experimentally extracting constituent processes, and attempting to study them in isolation.

An epistemic issue vexing clinical and other functional neuroimaging is that of reverse inference. Reverse inference occurs when the cognitive functions whose neurocircuitry is being charted are inferred from the monitored neurocircuitry itself. Stipulating a target function in quantitative terms definitively anchors the entity whose neurophysiological substrates are being probed at the cognitive behavioral level of analysis, rather than at the temporal–spatial co-occurrence of neurocircuitry signals.

Dynamical Monitoring of Individual Treatment

Monitoring cognitive behavioral task performance can be used to ascertain individual

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functioning over a course of treatment. Estimation of model properties pertinent to information processing, memory, perceptual and other faculties of mentation can provide cognitive science principled assessment of progress.

Tracking treatment response is potentially expedited by uploading the performance model onto a Bayesian statistical platform. Doing so exploits tenable theoretical distributions of individual differences in model parameter values among demographic or diagnostic populations of clinical interest (known as parameter mixing distributions, hyperdistributions, or Bayesian priors). Expanding clinical mathematical modeling to a hierarchical design, which strategically provides for individual differences, brings into play several noteworthy advantages from a clinical perspective.

Importing pre-existing information lodged in Bayesian prior distributions of model parameter values allows for relatively precise parameter estimation for a specific individual, using only a modest specimen of his or her task performance (a statistical property known as “Bayesian shrinkage”). Modesty of task demands may be considered especially welcome when dealing with already distressed individuals. Integration of individual performance with prior information, through Bayes’ theorem, is analogous to bringing to bear on a small blood specimen rendered in a hematological clinic the full bank of pre-existing hematological assay knowledge.

Along with charting the individual’s parameter estimates as treatment proceeds, the person’s relative position with respect to varying symptomatic and asymptomatic groups can be tracked in a similar, dynamically adjusting fashion. An individual performance sample can be subjected through Bayes’ theorem to prior parameter distributions preliminarily crafted to benchmark groups of interest. This procedure is analogous to the actuarial clinical practice of referring scores from a multi-item psychometric test or inventory to selected standardization samples (e.g., normed

scores for age and gender on a scholastic achievement test help generate more informed expectations against which to test a recorded individual performance sample). In the present case, profiles of probabilities of belonging to the respective symptomatic and asymptomatic groups, given updated performance specimens—altogether yielding profiles of “Bayesian posterior probabilities”—thus can be probed at desired time points.

Similar dynamical assessment of treatment regimens also presents itself. The above cognitive and Bayesian statistical methodology can be expanded to assess whether a treatment program is edging its treated sample closer to healthier cognitive functioning. Such examination of treatment regimens becomes especially relevant to evaluation of central nervous system-related pharmacotherapy, as pharmaceutical companies increasingly have expressed interest in effects of such treatment agents specifically on cognitive efficiency (mathematical developments and computational specifics with empirical illustrations are presented in Neufeld et al., 2010).

Integration with Other Practices in Clinical Science and Assessment

Clinical mathematical modeling and multi-item psychometric measures can selectively complement each other. Empirical associations between model properties and scores from multi-item measures can augment one another’s nomothetic-span construct validity (Embretson, 1983). Correlations with model properties also may increase construct-representation construct validity of multi-item measures. Psychometric measures in turn could be used as proxy measures for model properties with which they sufficiently correlate, potentially resulting in savings of assessment resources (but cf. Bayesian estimation, above).

In addition, mathematical modeling can throw light on processes involved in responding to psychometric items. Specifically, modeling of item selection through item-response

theory can be complemented by modeling item-response time, viewed as a product of a stochastic dynamic process (Neufeld, 1998).

Clinical mathematical modeling also speaks to a longstanding issue of substantive inference, which is interlaced with measure-theoretic considerations. The problem is the so-called differential-deficit, psychometric-artifact confound. False inferences of differential cognitive deficit across alternate aspects of cognitive behavioral functioning are risked because differences across the addressed faculties, between clinical and control groups, are conflated with psychometric precision of instruments used to measure the faculties. More and less pronounced apparent differences actually may be attributable in good part to more and less group-discriminating psychometric measurement properties. The problem retains currency in clinical science. Recommended solutions using psychometric calibration of constituent measures (equating them for reliability and observed-score variance) have been challenged both on mathematical and empirical grounds. It has been argued instead that assigning components of psychometrically partitioned variance to mathematically modeled sources lends a model-based substantive interpretation to the components and renders the psychometric-artifact problem essentially obsolete. Partitioned variance now is fully prescribed according to a governing cognitive performance model. This model-partitioned variance includes classical measurement error variance (now across-trial, within-participant variance); within-group, interparticipant variance; and between-group variance (see Further Reading).

Future Directions and Challenges

Clinical mathematical psychology is increasingly represented in both clinical and mathematical psychology journals. Its application is arguably vital to expediting theoretical and empirical progress in clinical science and assessment, including the resolution of important, longstanding and intractable issues. It has

been stated that, as seen in other sciences, it is inevitable that psychological science will come to rely more and more heavily on mathematical modeling.

Psychology has witnessed repeated calls in its periodicals and newsletters for more quantitatively trained graduates. Traditional education in quantitative methods may or may not include mathematical psychology, but those trained in the latter almost always are versed in mathematical and psychological statistics. A strong case can be made for both an increasing role of mathematical psychology in the discipline at large, as well as the broader credentials carried by mathematical psychologists. For those lacking a formal background on the subject, mathematical psychology's inroads are accompanied by an ever-greater number of reference resources, tutorials, and workshops (see Further Reading).

The growing presence of mathematical psychology in clinical and nonclinical psychology seems in line with the esteem in which mathematical psychology is evidently held. Six of the sixteen U.S. Presidential Medals of Science awarded to psychologists have been given to mathematical psychologists, a figure far out of proportion to the representation of mathematical psychologists in the discipline. Regarding the two Nobel Prizes in Economics awarded for seminal psychological work, Herbert Simon (1978) and the late Amos Tversky (whose work on prospect theory with prizewinner Daniel Kahneman was recognized in 2002) were mathematical psychologists.

Ongoing challenges involve the productive integration of "cold and hot cognition." Roughly, cold cognition pertains to mechanisms of information processing and hot cognition pertains to inferences yielded, especially with respect to their semantic and affective attributes. Deviations in mechanisms of processing leading to dysfunctional representation of environmental events and personal significance can be of special clinical interest. Research done by Teresa Treat and colleagues on eating disorders and risk of sexual coercion exemplifies the integration of

symptom-meaningful hot and cold cognition (e.g., Treat & Viken, 2010).

Areas of investigation relatively untapped by mathematical modeling include mood and anxiety disorders. The documentation of symptom-relevant information processing in these families of disorders is poised to benefit from a quantitative charting of adverse changes in cognitive efficiency. Implications for intervention stand to follow, such as the disclosure of new, model-informed routes to treating and assessing symptom-relevant information processing (e.g., reduction in the ascendance of personalized negative associations).

Clinical mathematical psychology also raises the prospect of substantively driven meta-analysis techniques. Substantively driven meta-analysis entails explanatorily retrofitting available (mathematical) theory to pre-existing data, a bona fide scientific methodology known as “abductive reasoning.” Extracting model-based substantive information lodged in the literature’s data, much of whose format derives from a non-modeling perspective, remains an ongoing but important challenge.

It has been said that evidence-based practice is not best practice if it is not based on the best evidence. Best evidence implies maximizing the armamentarium of investigative options, notably including mathematical psychology adapted to the clinical arena. The complex nature of psychopathology and its treatment beckons the increased use of mathematical approaches as a sturdy platform for launching reliable and cohesive research agendas for the study of psychological illness and distress.

SEE ALSO: Bayes’ Theorem; Bayesian Analysis; Construct Validity; Differential Deficit; Evidence-Based Assessment; Item Response Theory; Kuhnian Paradigms; Meehl, Paul E. (1920–2003)

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1.3 Comment: “Clinical Mathematical Psychology” as Preface to Subsequent Component Documents

Looking ahead, there are seven specific examples within the next four component papers in this dissertation where principles or approaches described in the preceding paper, “Clinical Mathematical Psychology” (Shanahan, Townsend, & Neufeld, 2015) are instantiated. These are listed here, with descriptive explanation.

First, the use of Bayesian methodology to isolate set properties such as decision-structure identity in the decisional control model (Shanahan et al., 2015, p. 8), is extensively illustrated in Section 5, “Mixture-Model Properties (...) invoked by empirical touchstones”, in the second paper, “Towards a Comprehensive Model (...)” (Shanahan, Nguyen, & Neufeld, under revision).

Second, stochastic distributions and precise expectancies of threat allocation (Shanahan et al., 2015, pp. 1-2) are detailed in the third study, a dynamic, interactive catalog of decisional control values. This catalog provides a generalization analysis context for the specific instances selected as experimental values in the fourth and fifth papers, where values and structures are selected to investigate model-driven hypotheses.

Third, “custom-built”, axiom-driven model structures mentioned within the CMP encyclopedia entry (Shanahan et al., 2015, pp. 1, 3-4) are contained throughout the two conceptual and two empirical papers subsequent to the general introduction paper. These especially come to the fore in applying the design to experimentation, as in the stress prompting vignettes used to evoke motivated, paradigm consistent performance in participants. These structures were developed originally in order to quantify situations of partial or obstructed choice in hierarchies, and to examine the likely impact on both objective probability distributions and subjective perception and response to these. In brief, a non-modeling approach might have been to measure participant stress via questionnaire or behavioral instruments in a variety of decision-making environments with follow-up application of correlation or analysis of variance techniques.

Notwithstanding the requisite use of standard statistical procedures, used herein, Neufeld,

and colleagues have designed a *hierarchical model of various situations* and examined the logically-prescribed statistical exigencies thereof to inform experimental design.

Fourth, as a point of instantiation of components of the nascent field of clinical mathematical psychology, a spreadsheet platform in the third study (“Catalog of Decisional Control Values”, Shanahan, online spreadsheet in preparation) allows the immediate examination of the threat-expectancy distributions for all 9 first-order hierarchical scenarios (CC, CN, CU, NC, ..., UU), and all 27 second-order scenarios (CCC, CCN, CCU, CNC, ..., UUU). This interactive research tool will be made available via the established laboratory website for decisional-control work (publish.uwo.ca/~mshanah). This is an example of interactive research tools and resources, with apprehensible mechanisms readily examined in the transparent coding of spreadsheet cells (p. 9, 10).

Fifth, “abductive reasoning” (Shanahan et al., 2015, pp. 3, 10) in the fourth study “Information Processing (...) occurs in two important contexts: 1) in reference to the application of preference parameters to archived data sets and validating the new construct of a ‘maximizing continuum’ with existing data, and 2) in the derivation of a ‘decision value’ calculation to explain the finding of slope reversal in multi-modal dependent measures of stress, which suggested a two-source model for stress from information processing and threat exposure through abductive reasoning.

Sixth, the verification of model-prescribed phenomena in the two empirical studies would neither be specifiable, nor verifiable, without rigorous underlying theory and exact operationalization. The validation of both the *best-option availability as a good heuristic for situational threat* and the *systematic obstruction of threat reduction by lack of information*, not only lack of control (‘uncertainty’ over and above ‘no-choice’) were effects whose confident prediction was founded on theoretically-based simulation work (Shanahan, 2007; Shanahan & Neufeld, 2010). These expected effects have been substantially confirmed, with some qualifications.

Looking to give this purported achievement some context, a comparison may be made to pre-mapping, travelling to and reporting findings from hitherto uncharted territory, as in

the 15th and 16th century Age of Exploration, where the known territory is the standard body of stress and coping research. This study has predicted, described, operationalized and experimentally presented, measured, and confirmed what was expected almost purely from theoretical investigations in new stress and decision-making territory. Via simulational expectancies and hitherto lightly tested and validated model properties, real empirical phenomena were predicted that a) were not known, b) were not describable without the model, and c) were not measurable without rigorous theoretical anchoring. And there they are! Real participants, within empirically-revealed constraints, do indeed perceive stressful situations this way.

Seventh, the ground is charted to an initial degree and laid open in a multitude of directions because of the strong theoretical grounding that allows principled interaction between a plethora of phenomena of clinical interest: reaction time data, psychophysiological response, psychometric profiles, and the structure and parameter variations of decision-making scenarios. Though perhaps the most abstruse, this last achievement is the arguably the most valuable in that there is an immense, real, sturdy platform, now validated, upon which to build, launch, and otherwise transact potentially thousands of scientific research edifices, expeditions, and enterprises. This job, the validation of strong theoretical conjecture by real, multi-modal empirical results, is plausibly begun. Almost surely, more fruitful work remains open to being taken up in this newly opened but largely uncharted territory.

2 Towards a Comprehensive Model of Coping with Stress through Decisional Control: Exploiting Mixture-Model Properties of a Game-Theoretic Formulation

2.1 Introduction to the Second Component Document

Presented below in MS Word 2010 format is the manuscript “Towards a Comprehensive Model of Coping with Stress through Decisional Control: Exploiting Mixture-Model Properties of a Game-Theoretic Formulation”. Authors are Matthew Shanahan, Peter Nguyen, and Richard W.J. Neufeld. This paper was submitted to a Special Issue of the *Journal Mathematical Psychology* (in honor of William K Estes), but was not accepted in the context of the Special Issue. It is currently under revision for resubmission with added improvements. Notably, the appendices contain the core of the formulation framework for the decisional control model, in rapidly specifiable form. These are in turn instantiated in the third component document, “A Catalog of Decisional Control Values”.

Also notable within this second paper is the integration of decisional control between larger distribution structures of available decision features (i.e., decision structure set J , housing variation in choice condition ‘C’, ‘N’, ‘U’, and set size parameters P, p, q) and the micro-level occurrence count M , the yes-no observation of threatened outcome occurrence. This ‘sandwiching’ of the existing decisional-control model between higher-order meta-parameters and atomistic yes-no occurrence counts creates a simultaneously comprehensive yet highly adaptable structure for locating distributions and likelihoods of particular features within the model (threat values, decision structures) and for guiding future explorations.

2.2 “Towards a Comprehensive Model (...)”.

Inserted below is the complete manuscript. Within the formatting in this dissertation it is 52 pages long, and runs from page 16 to page 67, including a Footnotes page, an Appendix , Figure Captions page, and four Figures as the concluding material.

Study 2 – Theoretical Extension – Mixture Models

Abstract

Quantitative accounts of stress-related predictive judgments have stimulated consideration of the broader stress-navigation landscape in which such judgments operate. Decisional Control (DC), a means of coping with stress by “positioning oneself in a multifaceted stressing situation so as to minimize the probability of an untoward event,” is considered to occupy a prominent position in this landscape. Salient properties of DC have been implemented in a game-theoretic like infrastructure, emerging as a probability mixture model from which precise likelihoods of stress-relevant events and experiences have been derived. Also conveyed are Bayesian methods of characterizing DC-related properties of the stressor environment in which the events and experiences have taken place, including identification of hierarchical structures through comparative likelihood of sample generation. Uploading DC onto the presented quantitative platform forms a bridge between DC, as a cognition-intensive form of coping, with formal preference-and-choice models, and contemporary analyses of information processing.

Keywords:

stress negotiation; decisional stress control; coping; threat reduction; probability mixture models.

Toward a Comprehensive Model of Coping with Stress through Decisional Control:
Exploiting Mixture-Model Properties of a Game-Theoretic Formulation

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1. Introduction.

Psychological Stress and Coping comprises a major topic of investigation in the field of experimental personality research. Despite its complexity and intractability to verbal theorizing, formal developments on the topic nevertheless have been comparatively sparse.¹ Underscoring the complexity and challenge of this content domain, traditional treatments of psychological stress and coping have cast as fundamental to the richness of its phenomena interaction amongst the principle variables at work-- described, for example as “interplay of stress and coping responses”, and “transactional, person-environment interchange” (e.g., Lazarus & Folkman, 1984; Leventhal, 1970).

Central to this transactional characterization of stress phenomena has been the construct of “cognitive appraisal”. Cognitive appraisal purportedly consists of “primary appraisal of environmental threat”, and “secondary appraisal of coping options”, followed by re-appraisal according to apparent coping efficacy. As such, psychological stress and coping have been deemed to entail cognition (appraisal) intensive person-environment interplay. This understanding is parlayed into a game-theoretic schema of stress negotiation, known as “decisional control”. Quantitative foundations of the schema

disclose mixture-model properties, in that parameters of the model themselves are stochastically distributed, with their mixing distributions arising naturally from model architecture. Model predictions moreover lend themselves to multinomial likelihoods of empirical events, poised for model testing.

Because of their status as Bayesian priors, the model's mixing distributions usher in individualization of model operation. Available is a Bayesian customized profiling of model-related environmental properties, mediated through individual specimens of experienced events.

2. Cognitive appraisal of threat.

Objects of prediction in anticipatory appraisals surrounding stress pertain to aspects of the individual's environment that potentially generate adverse occurrences (e.g., those of physical danger or severe discomfort; or untoward social interchange). To what degree might principles of categorical predictions apply to those circumstances? Three paradigmatic changes stand to modify or unseat the operative mechanisms such as competition models used in past research (cf., Estes, 1976).

One such change concerns the nature of the objects of judgment. Where predictions are those of a victorious competitor, stimuli necessarily have been presented in pairs, thereby invoking two protocols of information. In predicting whether a stimulus encounter (e.g., physical location or social setting) will result in a stressing event, however, stimuli can be judged singly.

Second, stress related predictions are not necessarily of a discrete format, as they are in the case of Bernoulli-like win-loss occurrences. Rather than discrete outcomes to stimulus encounter, the *probability* of a stressing event more likely comes to the fore.

Third, the makeup of predicted outcomes also changes. For example, one category of outcome may consist of physically aversive events, while another takes the form of benign events.

Alteration in judgment structure *sui generis* to anticipatory stress appraisals potentially attenuates the judgment-process dominance of categorical frequencies of the predicted event, as seen in non-stress judgments (e.g., Estes, 1976). At the same time, judgments themselves may be more demanding, and thereby detract from comprehensive protocol implementation. Estes (1976) observed that individual probability judgments may depend on a series of covert all-or-none predictions. Consequently, increased economy by way of a reduced set of implicated protocols may be countered by greater complexity specifically of probability assessments, as appurtenant to the stress-coping domain.

Would previously established categorical-memory mechanisms nevertheless extend to this domain? The conclusion from a series of studies in which stress-context were instituted (Kukde & Neufeld, 1994; Lees & Neufeld, 1999; Morrison, Neufeld & Lefebvre, 1988; Mothersill & Neufeld, 1985; Neufeld & Herzog, 1983; see also, Neufeld, 1982; Neufeld & Mothersill, 1980) was affirmative. Here, alphabetic letters experimentally were endowed with histories of subjectively noxious incidents, comprising bursts of experimentally-delivered loud white noise (of documented

aversiveness, according to subjective, and Thurstonian-scaled autonomic responses; Lefave & Neufeld, 1980; Neufeld & Herzog, 1983), on the one hand, and of benign outcomes (illumination of a green light), on the other.

Paralleling the previous findings and model predictions, the relative *cumulative frequencies* of the untoward outcomes determined individuals' probability judgments of the untoward event, upon subsequent presentation of a contextual stimulus (alphabetic letter). For example, the anticipatory probability of noise occurrence to an alphabetic-letter stimulus correlated .97 with its earlier cumulative pairing with a noise outcome, .80 with the contingent probability of a noise outcome, and -.147 with its cumulative pairing with a silent outcome. Partial correlations of the judged probabilities with these respective properties, statistically adjusting for any inadvertent overlap with the other two properties, were .419, .013, and -.221 (Neufeld & Herzog, 1983). A similar pattern of values was observed for reported levels of subjective stress instigated by the contextual stimuli. The dominance of the first property, above, withstood experimental variations, including differential pronunciation of the stressing and benign outcomes during the history-endowing trials (Einhorn & Hogarth, 1978; Estes, 1976; Neufeld & Herzog, 1983), and predicting both untoward and benign-event probabilities, during the judgment trials (Mothersill & Neufeld, 1985).

Interestingly, ascertaining the relative position of a presenting stimulus, with respect to its comparative cumulative frequency of adverse outcomes, implies consideration of like properties for the remaining contextual stimuli. Establishing the contingent probability of adverse-event occurrence to a presenting contextual stimulus, in contrast, brings into play but two categorical-event protocols—its past accumulation of

stressing and of benign outcomes. Entry of the array of relative adverse-event cumulative frequencies into participants' anticipatory appraisals evidently took place even though a contextual stimulus' contingent probability of the predicted event seemingly was more cognitively economical. In any case, relative cumulative frequencies of stressor-events decidedly were transduced into predictive judgments of stressor occurrence, coherent with the operation of categorical-memory mechanisms in the sphere of stress appraisals. These findings stimulated consideration of the larger stress-negotiation landscape in which such cognitive stress appraisals are brought to bear.

3. Coping with stress through Decisional Control.

A prominent form of coping in which predictive appraisals play a vital role is "Decisional Control" (DC). This constituent of an early informal taxonomy of ways of coping, posed by Averill (1973), was deemed simply to vary with the number of alternatives available to an individual for engaging stressful situations (cf. Thompson, 1981). Subsequently, DC has been described somewhat more formally as "positioning oneself in a stressor situation so as to avoid situational components harboring higher probabilities of stress" (Lees & Neufeld, 1999, p. 185). Decisional control thus is regarded as cognition intensive, in its requirements for judged threat attached to the respective possibilities for stressor-situation engagement. In socially evaluative circumstances, for example, social exchanges may be judiciously broached so as to minimize the likelihood of a consequential social misstep, or gauche exchange. In a setting of physical threat (e.g., potentially dangerous industrial workplace), DC could take the form of successfully manoeuvring into the situational option (e.g., job task) carrying the least risk of injury or significant discomfort.

3.1. *Environmental context of decisional control*

We begin, in a game-theoretic vein, by posing situation scenarios that express the essential features of DC, and that spur quantitative treatments disclosing otherwise intractable inferences about its functioning. Such prototype scenarios take on the following design. Objects of potential choice are arranged hierarchically in a nested-nesting layout. Each tier of the hierarchy is divided into a discrete set of entities, eligible for the decision maker's (DM) engagement-- depending on conditions of accessibility operative at that tier (*DC condition*, elaborated upon below).

In a building-construction scenario, for example, nested within construction sites are job locations (e.g., atop a scaffolding, or a subterranean location). Specific jobs (e.g., transporting materials, versus positioning and assembling them, and so on) in turn are nested in job locations. Each tier of this hierarchical, nested-nesting design, from construction site down to job assignment, contains a specific number of potential options, and each is governed by prevailing constraints on option eligibility.

Minimizing threat, by exercising decisional control, ultimately entails engaging the specific situation element (job assignment), from among those made available by the constellation of DC conditions, that has the minimum judged probability of physical injury or significant pain. Scenarios of social-evaluation stress can be similar. At an academic or business convention, for example, gatherings may be nested in convention hotels; and potential interlocutors, bearing varying threats of an untoward interchange with the diffident delegate, are nested within gatherings.

The number of entities making up the respective strata in such a 3-tier design, from highest to lowest, are represented as quantities by P , p , and q (model parameters). The DC conditions, which are tier-wise mutually exclusive, are the following: unfettered choice of the tier's entities (C); external assignment of an entity, with uncertainty as to the assignment's identity during the decision process (U); and external assignment of the entity, with disclosure of its identity from the outset of the decisional process-- that is to say, no choice, and no uncertainty (N). For conditions U and N , external assignment of the tier's encountered constituent is random; this proviso is in keeping with an absence of both control and predictability, in the case of U , and the absence of control in the case of N .

Such a layout is depicted in Figure 1. Using bin (urn) terminology, returning to the building-construction example, construction sites represent bin sets; job locations, nested within construction sites represent bins; and jobs varying in judged probabilities of an adverse event, such as injury or significant pain, instantiate elements nested in bins. In this illustration, $P = p = q = 2$, making for 8 scenario elements. Levels of threat (i.e., adverse-event probabilities) attached to the respective elements, increasing from lowest to highest, are denoted t_i , $i = 1, 2, \dots, Ppq$.

3.1.1. Summary Expression of DC properties.

The above developments lend themselves to more parsimonious and conceptually tractable statements. Deployment of DC conditions for a 2-tier nesting-nested hierarchy can be expressed as follows:

$$\exists x_i \ni \forall x_i \in \{x_1, x_2\}, x_i = C \vee (U \vee N),$$

where $x_{1,2}$ denote the DC conditions for the upper and lower tiers, respectively.

The parallel statement for a 3-tiered hierarchy is

$$\exists x_i \ni \forall x_i \in \{x_1, x_2, x_3\}, x_i = C \vee (U \vee N),$$

where $x_{1,2,3}$ denote the DC conditions for the upper, middle and lower tiers, respectively.

Each of the pq elements of the 2-tiered hierarchy, and Ppq elements if the 3-tiered hierarchy, has a unique appraised probability of adverse-event occurrence t_i :

$$\{t_1 < t_2 < \dots < t_i < \dots < t_{(P)pq}\}; t_j < t_i \text{ iff } j < i; t_i \in [0,1].$$

Element encounters are deemed to result in Bernoulli outcomes m : presence versus absence of adverse-event occurrence. Occurrence implies 1.0 arbitrary unit of magnitude, and non-occurrence implies 0 units: $m \in \{0,1\}$.

The expected value of m , therefore is equal to

$$\sum_{i=1}^{(P)pq} Pr(t_i) [t_i(1.0) + (1 - t_i)(0)] = \sum_{i=1}^{(P)pq} Pr(t_i) t_i = E(t).$$

Variance in event magnitude $Var(m)$, in turn, is

$$\begin{aligned} & E[E(m^2|i)] - [E(E(m)|i)]^2 \\ &= \sum_{i=1}^{(P)pq} Pr(t_i) [t_i(1.0^2) + (1 - t_i)(0^2)] - \left\{ \sum_{i=1}^{(P)pq} Pr(t_i) [t_i(1.0) + (1 - t_i)(0)] \right\}^2 \end{aligned}$$

$$= \sum_{i=1}^{(P)pq} Pr(t_i)(t_i) - \left[\sum_{i=1}^{(P)pq} Pr(t_i)t_i \right]^2 = E(t)[1 - E(t)].$$

$Var(m)$ is appurtenant to the psychological-stress context because unpredictability of adverse-event occurrence during an addressed epoch can be stressing in its own right (see. e.g., Denuit & Genest, 2001; Osuna, 1985; Paterson & Neufeld, 1987; Smith, 1989; Suck & Holling, 1997). While $E(m)$ for $m \in \{0,1\}$ is equal to $E(t)$, above, $Var(m)$ is an “inverted-U” function of $E(t)$, and is maximum where $E(t) = 0.5$.

4. Empirical touchstones of Decisional-Control architecture’s random variables.

It is apparent that random variables in the DC architecture comprise engagement of element i and second, stressing versus benign occurrences $m \in \{0,1\}$, occurring to the engagement. Note that the probability of engaging element i $Pr(i)$ is identical to the probability of encountering its unique threat level, or $Pr(t_i)$. The latter is used throughout to highlight the focus on this property. Its computation is taken up below. Meanwhile, again the probability of a stressor outcome, given element i , $Pr(m = 1|t_i)$, is t_i .

Where DC conditions include provision for choice, $Pr(t_i)$ entails first the probability of its emerging as one of the t_i being available for selection, amidst other DC constraints; and, second, the probability of its being the lowest value of the presenting t_i -- $\min(\text{available } t_i)$. Where choice is prevented, the engaged t_i falls to random assignment.

It is assumed that stressor-event magnitude is such that probability of its occurrence is minimized. Accordingly, where condition U applies to an object of choice (e.g., elements nested in bins, where DC-condition C attends bins and/or bin sets), choice is made in favor of the bin nesting the minimal t_i value, from among those bins availed by DC conditions (e.g., Morrison, et al, 1988).

Model-stipulated $Pr(t_i)$, and $Pr(m = 1)$, bear on empirical events, namely engaged t_i 's, and attendant $m = 1, 0$. We use the following format in denoting the number of experiences (trials) of a specific set of DC conditions C, U, N , as combined with (typically single-integer-valued) parameters $(P)p, q$: $Z_{DC\ combination; Ppq}$. For instance, the number of experiences of a 3-tiered hierarchy with DC combination CNU , and parameters $P = p = q = 2$, is denoted $Z_{CNU; 222}$. A useful more general expression takes the form $Z_{C, U, N; (P)pq}$. Within any particular combination of DC conditions C, U, N , and parameters $(P)p, q$, the number out of the total $Z_{C, U, N; (P)pq}$

experiences resulting in the engagement of t_i is denoted n_i ; $\sum_{i=1}^{(P)pq} n_i = Z_{C, U, N; (P)pq}$.

Likewise, within the t_i engaged during a specific —tier-parameter [i.e., $C, U, N; (P)pq$] experience, the number of sampled Bernoulli-event outcomes is denoted $M_{C, U, N; (P)pq}$. The frequency of $m = 1$ amongst these t_i -dominated outcomes is denoted m_1 , and that of $m_0 = 0$ is denoted m_0 ; $m_1 + m_0 = M_{C, U, N; (P)pq}$.

4.1. Computation of the probability of engaging threat level t_i , $Pr(t_i)$.

The following groups of DC conditions represent the forms of $Pr(t_i)$ derivations emanating from the 2- and 3- tier hierarchical nesting-nested designs. They include, (a), unfettered choice CC and CCC ; (b), choice combined with neither choice nor uncertainty NC , CCN ; (c), choice combined with uncertain assignment CU , and CCU ; (d), all 3 DC conditions UCN , and NCU ; and, (e), random assignment NNN , whose $Pr(t_i)$ is identical to that of UUU (extensions of their 2-tier hierarchy counterparts).

(a). CC and CCC : $Pr(t_1) = 1.0$, and $Pr(t_{i'}) = 0$, where $i' = 2, \dots, (P)pq$. That is, the lowest of the $(P)pq$ values always is available.

(b) NC : $Pr(t_1) = 1/p$. Assuming random assignment, above, the probability of t_1 's bin being assigned is $1/p$, and t_1 necessarily is the least of the bin's q t_i values.³

$Pr(t_{i'})$ entails the current $t_{i'}$'s availability for possible selection, and its being the lowest of the selectable $t_{i'}$ values. The probability that the current $t_{i'}$ is selectable brings into play the probability that t_1 's bin has not been assigned $(p-1)/p$; the probability that the current $t_{i'}$ occurs in one of the bins not occupied by t_1 , or $(p-1)q/(pq - 1)$; and the probability that the bin containing the current $t_{i'}$ has been assigned, given that the bin containing t_1 has not been assigned, or $1/(p-1)$ – altogether

$$\frac{p-1}{p} \cdot \frac{q}{pq-1} \cdot$$

The probability that the current $t_{i'}$ is the lowest of the q $t_{i'}$ values in its bin invokes the Hypergeometric distribution (e.g., Patil & Joshi, 1968). This distribution is used to

assess the probability that all other elements in the bin nesting the present t_i exceed its value, given its location outside t_1 's bin.

Paralleling bin (urn) -model terminology, $H(q-1; pq-2, pq-i', q-1)$ is the probability that out of a random sampling of $q-1$ (mutually independent) balls, without replacement (cf., Milenkovic & Compton, 2004) -- that is, $q-1$ (mutually independent) threat values t_i -- from a bin containing a total of $pq-2$ balls (both t_1 and the t_i under consideration themselves are ineligible), $pq-i'$ of which are white, -- that is, $pq-i'$ for which t_i exceeds the particular t_i under consideration, -- all $q-1$ sampled balls are white -- that is, all sampled t_i values exceed the currently entertained t_i . An analogous format of the hypergeometric distribution is used when the latter is called upon in obtaining the remaining mathematical expectations of threat.

$$CCN: \text{ By similar logic, for this DC combination, } Pr(t_1) = \frac{1}{q}, \text{ and } Pr(t_i) = \frac{q-1}{q} \cdot \left(\frac{q-1}{q} \cdot \frac{1}{q-1} + \frac{(Pp-1)q}{Ppq-1} \cdot \frac{1}{q} \right) \cdot H(Pp-1; Ppq-2, Ppq-i', Pp-1).$$

The quotient $(q-1)/q$ expresses the probability of t_1 not being the assigned element in its bin. The expression in large brackets obviously simplifies to $Pp/(Ppq-1)$. Its expansion nevertheless discloses contingencies on which t_i ' engagement depends (as also is seen with similar expansions, below). They comprise the probability of the current t_i residing in the bin also occupied by t_1 , $(q-1)/(Ppq-1)$, multiplied against the probability of the current t_i 's assignment, given both its occurrence in t_1 's bin and non-assignment of t_1 , $1/(q-1)$, plus the probability of the current t_i being positioned in a bin other than the one containing t_1 , given non-assignment of t_1 , $(Pp-1)q/(Ppq-1)$, multiplied

in turn against the probability of the current t_i being assigned, given its position outside t_1 's bin, $1/q$.

$H(Pp-1; Ppq-2, Ppq-i', Pp-1)$, in turn, gives the probability of the present t_i being lowest of the Pp candidates for selection, given that t_1 is not one of them.

(c.) *CU*: Extending like reasoning to representative DC-condition combinations involving uncertain assignment, in the case of *CU*, $Pr(t_1) = 1/q$. Recalling that *U*-related bin selection serves potential engagement of the lowest bin-held t_i (in the present instance, t_1), $Pr(t_i) = (q-1)/[q(pq-1)]$.

CCU: In like fashion, here, $Pr(t_1) = 1/q$, and $Pr(t_i) = (q-1)/[q(Ppq-1)]$.

(d.) *UCN*: Turning to representative combinations with the presence of all DC conditions, for *UCN*, $Pr(t_1) = 1/(Pq)$, whereas $Pr(t_i) =$

$$\frac{1}{P} \cdot \frac{q-1}{q} \cdot \frac{p}{Ppq-1} \cdot H(p-1; Ppq-2, Ppq-i', p-1) + \frac{P-1}{P} \cdot \frac{(P-1)p}{Ppq-1} \cdot \frac{1}{P-1} \cdot H(p-1; Ppq-2, Ppq-i', p-1).$$

NCU: As with *UCN*, $Pr(t_1) = 1/(Pq)$. Different from *UCN*, $Pr(t_i) =$

$$\frac{1}{P} \cdot \frac{q-1}{q} \cdot \frac{1}{Ppq-1} + \frac{P-1}{P} \cdot \frac{pq}{Ppq-1} \cdot \left[H(pq-1; Ppq-2, Ppq-i', pq-1) \cdot \frac{1}{q} + \left\{ (1 - H(pq-1; Ppq-2, Ppq-i', pq-1)) \cdot \frac{q-1}{pq-1} \cdot \frac{1}{q} \right\} \right].$$

Of note is the expression in braces. It conveys the possibility of the current t_i being engaged, regardless of its value. Proceeding successively, included therein is the

probability that the current t_i is not the lowest among the elements in the assigned bin set, given that the latter is a set other than that in which t_1 is located, and given the current t_i 's own location in the assigned set. Included as well is the probability of the current t_i 's being one of the other $q-1$ elements in the bin containing the lowest of the assigned bin set's pq elements, along with the probability of the current t_i emerging as that bin's designated element, given its location therein.

In the case of *NCU*, then, even the highest $p-1$ t_i values stand to be encountered, through sheer dint of embedding with the designated bin set's lowest t_i value. Combination *UCN*, on the other hand, allows the decision making stress negotiator to espy the occurrence of such a high t_i value, and thereby to take evasive action, in favor of the least of the designated p values. Here, the highest $p-1$ values are never encountered.

(e.) *NNN;UUU*: In each case, $Pr(t_1) = Pr(t_i) = 1/(Ppq)$.

A complete listing of the $Pr(t_i)$ formulae, for the 2 and 3-tier hierarchies, is presented in the Appendix to this document.

5. Mixture-model properties of Decisional-Control architecture invoked by empirical touchstones.

The DC model has been supported by both empirical and large-simulation data (Kukde & Neufeld, 1994; Morrison, et al, 1988; Shanahan & Neufeld, 2010). Empirical data has taken the form of psychophysiological (autonomic and facial-electromyographic) measures, along with subjective and behavioral (element-selection latency) measures. Measurement-battery evidence of stressor-event threat has

approximated DC-modeled threat expectation $E(t)$, above; evidence of covert information processing mediating DC-availed threat reduction, in turn, has approximated the DC-quantified predictive judgments on which it is contingent. Simulation data has conformed to relations between the above threat and processing indexes across an extensive grid of P , p and q parameter values (large-scale simulation; Shanahan & Neufeld, 2010a). Embedded in such simulations has been model sensitivity and generalization analysis, endorsing robustness of model performance across nesting-hierarchy complexity; extensive variation in parameter values; and selected constraints on parameter relations (e.g., $P < p < q$).

Additional empirical support emanates from an experiment whose principal data have addressed individual differences in threat-versus-challenge cardiovascular responses (Blascovich, Seery, Mugridge, Norris & Weisbuch, 2004) to variation in DC structures (Shanahan, Nguyen & Neufeld, in preparation).⁵ Presented with a 2-tiered layout, 39 female and 32 male Psychology undergraduates selected structure elements t_i , having unique threat associations (cf. **2. Cognitive appraisal of threat**, above), within each of the 9, 2-tier DC scenarios. Each structure was presented in conjunction with 6 p , q combinations, ranging from 2,2, to 9,7.

The model-prescribed expected value of i (element order in the ascending element-threat array; $i = 1, 2, \dots, pq$) was computed for each structure, under each

combination of p and q :
$$E(i) = \sum_{i=1}^{pq} Pr(t_i)_{C, U, N; pq}^i .$$
 The values of $E(i)$ then were

averaged over the 6 p , q combinations, separately within each DC structure. A substantial

correspondence was obtained between these model-generated, and empirical values, across the 9 DC structures, $pseudo-r^2 = .81$ (for definition of $pseudo-r^2$, see Cobb, 1981).

When correction was made for chance departure of the experimental paradigm from model-stipulated values [e.g., paradigm designation of t_i in condition NN was based on random t_i selection, with chance departure from a consistent probability of strictly $1/(pq)$], $pseudo-r^2$ was .99.

Other empirical support has been indirect. It has occurred by way of numerical simulation, and empirical diary and ecological-momentary-sampling support (Levy, Yao, McGuire, Vollick, Jetté, Shanahan, Hay & Neufeld, 2012), of a nonlinear dynamical systems model of stress and coping in which DC has figured prominently (Neufeld, 1999).

With such sources of endorsement in hand, addressed here are more extensive quantitative properties of the DC formalization, and their further empirical linkages. The present developments are directed to modeled probabilities of events-- t_i engagements and occurrences of stressor-benign-incidents $m = 0, 1$. Note that where the events comprise encountered stressing and benign incidents m_1 and m_0 , the *probabilities* of such occurrences t_i themselves are stochastically distributed as $Pr(t_i)$ -- altogether resulting in a mixture-model architecture. Model properties governing $Pr(t_i)$ are DC conditions C, U, N , and tier-size parameters, P, p and q . In line with this configuration, C, U and N , and P, p , and q assume the role of hyper-parameters, of the model-prescribed mixing distribution of base-distribution parameters t_i .

Where the addressed observed variates comprise engaged elements t_i themselves, the architecture is truncated at that observational level. Figure 2 presents the DC layout where t_i are the observed variates, and Figure 3 depicts the mixture-model extension, where $m = 0, 1$ are the observed variates.

5.1. Multinomial likelihood of engaged DC-situation elements n_{t_i} .

For observed variates t_i , occurring under a given combination of DC conditions and tier parameters, the multinomial likelihood $ML_{C, U, N; (P)pq}$ of the $(P)pq$ empirical values of n_{t_i} is

$$\frac{Z_{C, U, N; (P)pq}!}{(P)pq \prod_{i=1}^{(P)pq} n_{t_i}!} \cdot \prod_{i=1}^{(P)pq} Pr(t_i)^{n_{t_i}}. \quad (1)$$

Where there are J DC-structures, the j th of which has prior probability π_j , $j = 1, 2, \dots, J$, (tier-parameter values being equal), the above multinomial likelihood becomes

$$\sum_{j=1}^J \pi_j ML_j. \quad (2)$$

5.2 Binomial likelihood of stressor and benign incidents m_1, m_0 .

In like fashion, for observed variates $m = 1, m = 0$, occurring under a given episode of DC conditions and tier parameters, the binomial likelihood $BL_{C,U,N;(P)pq}$ of the m_1 and m_0 empirical values is

$$\sum_{i=1}^{(P)pq} Pr(t_i) \binom{M_{C,U,N;(P)pq}}{m_1} t_i^{m_1} (1 - t_i)^{m_0} . \quad (3)$$

Again, for J DC-condition—tier-parameter combinations, the j th of these having probability π_j ,

$j = 1, 2, \dots, J$, the above binomial likelihood becomes

$$\sum_{j=1}^J \pi_j BL_j . \quad (4)$$

5.3. Formation of likelihood ratios.

Creation of a multinomial and binomial likelihood ratio (LR) ushers in assessments of empirical model fit, as follows. Available are computations of G^2 , which is asymptotically χ^2 with an increasing number of observations [e.g., $Z_{C,U,N;(P)pq}$ of equation (1); $M_{C,U,N;(P)pq}$ of equation (3)]; $G^2 = -2 \ln (LR)$. The ML or BL expressions, above, form the numerator of the LR . The saturated generic model forming the denominator is identical to the numerator, except now $Pr(t_i)$ is replaced with

$$\frac{n_{t_i}}{Z_{C, U, N; (P)pq}}$$

and t_i is replaced with

$$\frac{m_1}{M_{C, U, N; (P)pq}}.$$

As there are no parameter estimates, both Akaike and Bayesian Information Criteria reduce to G^2 .

Also available is the Bayes factor. With equal prior probabilities of two competing models, it comprises

$$\frac{Pr(\text{empirical evidence} | \text{Model 1})}{Pr(\text{empirical evidence} | \text{Model 2})}. \quad (5)$$

As implemented here, the numerator of equation (5), for example, potentially consists of the *ML* or *BL* of the actual data-generating DC conditions, with the denominator consisting of the *ML* or *BL* of a different set of conditions, (P), p , q being equal. Such an arrangement conveys the degree to which element engagements, or stressor-benign—event occurrences, selectively conform to predictions from prevailing DC conditions.

5.4. Numerical examples and Bayesian profiling in stressor situations.

5.4.1. Implementing frequencies of Decisional-Control structure -element engagement.

The following example illustrates construction of the multinomial likelihood $ML_{C,U,N;(P)pq}$ and related statistics for the frequencies of DC-structure-element encounter

n_{t_i} . Sufficient for illustration is the construction of these expressions for the two-tier nesting hierarchy, using the first two listed DC structures, *CC*, and *CU*. Computations are presented for $p = 4$, $q = 3$. Note that like procedures apply to other values of p and q , and to increased hierarchy complexity.

In the present case,

$$Z_{CC;43} = 25; \quad n_{t_1} = 22; \quad \sum_{i=2}^{12} n_{t_i} = 3.$$

Because $Pr(t_1)_{CC;43} = 1.0$, we dichotomize the values of i into $i = 1$, and the remainder, $i = 2, 3, \dots, 12$. Moreover, to avoid singularities incurred by $Pr(t_{i;i=2,3,\dots,12}) = 0$, predictions simply assume a close approximation of model predictions (cf. Morrison, et al., 1988).

Here, $Pr(t_1) = 1.0$ is replaced with $Pr(t_1) = .95$, making $1 - Pr(t_1) = .05$.

The resulting $ML_{CC;43} = .09301$, and $ML_{generic, saturated model} = .2387202$. The value of $G^2 = 1.885$, which renders a p value of .17 when referred to the distribution for $\chi^2_{(df=1)}$. We note that such p values should be interpreted with some care especially considering multinomial-likelihood- χ^2 empirical cell-frequency assumptions (e.g., Delucchi, 1993; García Pérez, 1994; 2000; Tollenaar & Mooijaart, 2003).

Turning to *CU*,

$$Z_{CU;43} = 25; n_{t_1} = 10; n_{t_{i,i=2,3,\dots,12}} = 2,1,0,$$

in 5 instances, and then again in 5 instances, and in 1 instance, respectively. $Pr(t_1)_{CU;43} = .33$, and $Pr(t_{i=2,3, \dots, 12}) = .06$. The value of $ML_{CU;43}$ is $9.6192(10^{-7})$. That of $ML_{generic, saturated model}$ is $.0000154$, resulting in a value for G^2 of 5.5464 ;

$$p_{\chi^2_{(df=11)}} = .9018.$$

Applying CU predictions to

$$n_{i; i=1, 2, \dots, 12}; CC; 43$$

leads to a G^2 value of 32.83 . Likewise, applying CC predictions to

$$n_{i; i=1, 2, \dots, 12}; CU; 43$$

produces a G^2 value of 62.1 . The $\chi^2_{(df)}$ p values for these amounts approaches 0 in each case.

Allowing the same Bayesian for each DC structure, the Bayes factor for the CC -generated empirical data,

$$\frac{ML_{CC; 43; CC - generated data}}{ML_{CU; 43; CC - generated data}},$$

is $5.2637(10^6)$. That for CU -generated data,

$$\frac{ML_{CU; 43; CU - generated data}}{ML_{CC; 43; CU - generated data}},$$

is $1.942(10^{12})$. DC-structure discrimination in each case obviously meets the Bayes-factor criterion of “decisive”.

Altogether, the present proof-of-principle, illustrative instantiation, indicates that multichotomous data tenably emanating from one or the other DC structure distinguish that structure (cf. Cohen, 1988, chap.7).

5.4.1.1 .Bayesian profiling of DC aspects of the stressor situation, as mediated by DC-structure element- engagement frequencies.

Monitored DC-structure element engagements $n_{t_i; i = 1, 2, \dots, (P)pq}$

in principle afford Bayesian estimation of DC-structure features of stressor environments.

Allowing equal values of (P) , p and q , and DC model operation, the posterior probability of the j th of J mutually exclusive and exhaustive candidate DC structures

$$Pr(C, U, N; (P)pq)_j \left| \left\{ n_{t_1}, n_{t_2}, \dots, n_{t_{(P)pq}} \right\} \right.$$

is

$$\frac{\pi_j ML_j}{\sum_{j=1}^J \pi_j ML_j} .$$

Where the Bayesian priors π_j are equal, considering the constant normalizing factor,

$$Pr\left((C, U, N; (P)pq)_j \left| \left\{ n_{t_1}, n_{t_2}, \dots, n_{t_{(P)pq}} \right\} \right. \right) \propto ML_j .$$

5.4.2. Implementing frequencies of stressor and benign incidents.

Implementation of stressor and benign incidents, over the course of their

$M_{C,U,N;(P)pq}$

independent opportunities, is illustrated for the 3-tier hierarchy, with $P = p = q = 2$. The value of $t_1 \equiv .1$, with $\Delta t_i \equiv .1$ (e.g., Shanahan & Neufeld, 2010a).

For $m_{1;CCC;222} = 2$, $m_{0;CCC;222} = 23$, and $m_{1;UUU, \dots, NNN;222} = 14$, $m_{0;UUU, \dots, NNN;222} = 11$, conditions with contrasting presence of choice, CCC versus UUU, \dots, NNN , are clearly distinguishable. The $BL_{CCC;222}$ is .25315; $BL_{generic, saturated model} = .28203$; $G^2 = .21603$, $p_{\chi^2(df=1)} = .642$. The $BL_{UUU;222}$ is .0480755, and $BL_{generic, saturated model}$ is .1591081; $G^2 = 2.396$, $p_{\chi^2(df=1)} = .1218$.

Applying UUU predictions to $m_{1,0;CCC;222}$ leads to a value for G^2 of 3.7593,

$p_{\chi^2(df=1)} = .0525$.

Using CCC predictions for $m_{1,0;UUU;222}$ renders G^2 as 8.13,

$p_{\chi^2(df=1)} = .0043$.

The Bayes factor,

$$\frac{Pr(m_{1;CCC,222} = 2, m_{0;CCC,222} = 23 | CCC; 222)}{Pr(m_{1;CCC,222} = 2, m_{0;CCC,222} = 23 | UUU; 222)}$$

$$= \frac{.25315}{.04306} = 5.87 \text{ ("substantial")}. \quad \text{That comprising}$$

$$\frac{Pr(m_1; UUU, 222 = 14, m_0; UUU, 222 = 11 | UUU; 222)}{Pr(m_1; UUU, 222 = 14, m_0; UUU, 222 = 11 | CCC; 222)}$$

$$= \frac{.0480755}{.0027307} = 17.6055 \text{ ("very strong").}$$

Not surprisingly, numerical explorations indicate that less extreme differences in DC structures (e.g., CCC vs. CCU) are empirically less discriminable. Note that the mixture-model architecture applicable to empirical data, $m_{1,0;C,U,N;(P)pq}$, unfortunately does not lend itself to conventional statistical power calculations as a function of $M_{C,U,N;(P)pq}$ (e.g., Cohen, 1988; chap. 7).

All in all, DC structures are identifiable inasmuch as they differ in their expressions of $Pr(t_i)$ (see Appendix). Statistical discriminability, however, will be an increasing function of divergence in these expressions. An asset of the present formalization surrounding DC structures arguably comprises self-disclosed sources of strengths and weaknesses in the structures' empirical separability.

5.4.2.1. Bayesian profiling of DC aspects of the stressor situation, as mediated by frequencies of stressor and benign incidents.

Similar to the case for DC-element engagement, for the j th of J mutually exclusive and exhaustive DC structures,

$$Pr((C, U, N; (P)pq)_j | \{m_1, m_0\}) = \frac{\pi_j BL_j}{\sum_{j=1}^J \pi_j BL_j} .$$

Again, with equal π_j , and considering the constant normalizing factor,

$$Pr((C, U, N; (P)pq)_j | \{m_1, m_0\}) \propto BL_j.$$

It also is possible to profile values of t_i , given $m_{1,0}$. For example, episodic incidents $m=1, m=0$ may be available, contra the engaged context in which they occurred, because the former happen to be more poignant in memory. It may be desirable nevertheless to re-create-- in a Bayesian posterior-probability sense-- the degree of abiding threat in the individual's surroundings. Doing so now is tantamount to estimating the probability of each t_i , given the record of $m=1, m=0$, incidents. For a prevailing DC structure, then, $Pr(t_i | \{m_1, m_0\}, C, U, N; (P)pq) =$

$$\frac{Pr(t_i)_{C, U, N; (P)pq} BL_{t_i}}{\sum_{i=1}^{(P)pq} Pr(t_i)_{C, U, N; (P)pq} BL_{t_i}},$$

where

$$BL_{t_i} = \binom{m_1 + m_0}{m_1} t_i^{m_1} (1 - t_i)^{m_0}.$$

For J candidate DC structures, $Pr(t_i | \{m_{1,0}\}) =$

$$\frac{1}{\Theta} \sum_{j=1}^J \pi_j Pr(t_i|j) BLt_i,$$

where the normalizing factor $\Theta =$

$$\sum_{j=1}^J \pi_j \sum_{i=1}^{(P)pq} Pr(t_i|j) BLt_i.$$

Discussion

The mixture model we delineate is a methodical cognitive- and statistical-science approach to otherwise nebulous concepts in the field of psychological stress and coping, such as “cognitive appraisal of threat”. This formal stipulation of predictive-judgment mechanisms has seeded the development of stress-theoretic infrastructures in which predictive judgments play a central role. Research on “The Cognitive Side of Probability Learning” (Estes, 1976, p. 76) arguably has spawned substantively significant quantification of theoretical “stressology”, and moreover has pointed to candidate applied assessment technology for estimating coping-relevant attributes of the stressor environment. The current focus has been on negotiating psychological stress through a prominent, cognition-intensive form of coping, Decisional Control – situating oneself in a multifaceted stressing situation so as to minimize the probability of an untoward event. Uploading essential properties of this form of coping onto a quantitative platform, with its accompanying assumptive framework, has produced explicit likelihoods of engaging constituent, threat-harboring elements of the stressor situation, and also of untoward and benign incident occurrences. Such likelihoods, in turn, in principle are amenable to Bayesian characterization of DC-relevant properties of the environment, in which the engaged situation elements, or incident occurrences, have taken place.

Quantification of DC's workings also has potentiated a certain bridging to formal models of preference and choice, and information processing, as follows. Note that threat reduction demands an associated undertaking of cognitive transactions (Shanahan & Neufeld, 2010a). The generation of predictive judgments entails cognitive exertion, which represents a source of stress activation in its own right (Kukde & Neufeld, 1994; Solomon, Holmes & McCaul, 1980; Wright, 1984); DC-implementing mentation, and mitigation of stressor-incident threat, are reciprocally related (Morrison, et al, 1988; Shanahan & Neufeld, 2010a). In this way, the net appeal of DC as a means of coping brings into play "incompatibility of criteria" (Tversky, 1969; Tversky & Russo, 1969). This DC property has motivated its integration with formal accounts of preference and choice that highlight incompatibility of criteria, and accommodate DC's admixture of stochastic --elevated probabilities of lower t_i values-- and deterministic--reduced predictive-judgment demands-- commodities (Batsell, Polking, Cramer & Miller, 2003; Tversky, 1972a; 1972b). Through DC quantification of these inversely related commodities, intersection with formal preference-and-choice models has provided a means of stipulating psychometrically monitored individual differences in penchant for DC, in terms of the commodities' formally modeled utilities (Morrison, et al, 1988; Shanahan, Pawluk, Hong & Neufeld, 2012).

Cognitively ascribing threat of untoward events to constituent situation elements invokes a constellation of visual and memory search operations. Quantitative attributes of DC potentially dovetail with certain developments in contemporary cognitive science (Systems Factorial analysis, and assessment technology (SFT); Townsend & Altieri, 2012; Townsend & Wenger, 2004; Townsend & Nozawa, 1995). Fundamentals of

cognition implemented in SFT include cognitive capacity (cognitive work completed per unit time), mental architecture (serial, versus alternate parallel forms of dispatching cognitive-task constituents), termination criteria (degree of processing, on whose sufficiency informed responding is contingent), and cross-facilitation versus cross-impedance of component processing channels.

Cognitive work, comprising predictive judgments that put into effect available DC, stands to be specified through a mathematically disciplined yardstick, the integrated hazard function. Potentially availed by SFT is a formally grounded index of cognitive work as an endogenous source of stress activation.

Another presenting point of contact with SFT concerns the identification of stopping rules. Maximizing DC-afforded threat reduction lies in exhaustive processing of accessible situation threat elements t_i . As noted, however, meeting such demands demonstrably is stressing in and of itself. Depending on individual utilities of reducing exogenous sources of stress, t_i , versus endogenous sources, cognitive exertion, individuals may differentially forfeit a maximizing processing strategy (i.e., ensuring the least possible threat; Janis & Mann, 1977) in favor of a satisficing strategy (i.e., accepting a “sufficient”, if not maximum degree of threat reduction; Simon, 1955). Possible, as well, is a simplifying strategy, whereby the threat-reducing benefits of DC are relinquished in favor of minimal information processing (Shanahan & Neufeld, 2010; c.f., Paquette & Kida, 1988, Wright, 1975).

Cognitive activities underlying cognition-intensive threat reduction originate in the company of threat. Stress, therefore, stands to compromise its own resolution through

adversely affecting cognitive efficiency. Two (formally modeled) effects of stress on cognitive functioning, among others, include task-wise capacity reduction and suboptimal deployment of attentional resources across task elements that differ in their (quantified) importance to task execution (Neufeld, 1994; Neufeld & McCarty, 1994; Neufeld, Townsend & Jetté, 2007). Encroachment on DC-effecting processing capacity risks a shortfall, undercutting what is needed to exploit DC threat-reducing opportunities. Overall, the potentially complex interplay of endogenous and exogenous stressors, and stress effects on cognitive capacity that fuels cognition-intensive coping, ultimately bespeaks the continuous interactions of a “low-dimensional (nonlinear) dynamical system”, in which DC plays a central role (Levy, et al, 2012; Neufeld, 1999).

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Footnotes

1. Notable exceptions, emerging primarily from the ranks of mathematical psychologists, mathematicians, marketing researchers, and engineers, in the main have addressed waiting-induced stress and its costs (e.g., Denuit & Genest, 2001; Janikiraman, Myer & Hoch, 2011; Suck & Holling, 1997; Zohar, Mandelbaum, & Shinkin, 2002; all following Osuna's (1985) seminal work on the issue; see also Booth, 1985), as well as selected stress-measurement methods (Birnbaum & Sotoodeh, 1990).

2. It is assumed throughout that bin sets have an equal number of nested bins p , and that bins have an equal number of nested elements q . This assumption makes for computational tractability without imperiling generality of essential inferences (Shanahan & Neufeld, 2010a).

3. Additional observations on the current hypergeometric-distribution implementation are presented in Shanahan & Neufeld (2010b).

Appendix. Formulae for the probabilities of engaging Decisional-Control- structure element i , $Pr(t_i)$.

1. *Two-tiered nested-nesting hierarchy:*

$$Pr(t_i)_{CC;pq} = \binom{pq-i}{pq-1} \div \binom{pq}{pq}.$$

Note, for all formulae, the calculation convention assumed for simplicity of notation is that

$$\binom{N}{N} = 1, \binom{N-1}{N} = 0.$$

$$Pr(t_i)_{CN;pq} = \binom{pq-i}{p-1} \div \binom{pq}{p}.$$

$$Pr(t_i)_{CU;pq} = \frac{(q-1)}{q(pq-1)} + \binom{pq-i}{pq-1} \left(\frac{p-1}{pq-1} \right).$$

$$Pr(t_i)_{NC;pq} = \binom{pq-i}{q-1} \div \binom{pq}{q}.$$

$$Pr(t_i)_{NN;pq} = \frac{1}{pq} + \binom{pq-i}{pq}.$$

Note, where inert terms appear, as in $NN;pq$, above, the following term is inert for $i = 1, \dots, pq$:

$$\binom{pq-i}{pq}.$$

The intent is to create points of common comparison across the system of equations. In the $CU;pq$ equation, the second term in the addition (with a combination function) is inert for $i = 2, \dots, pq$.

$$\Pr(t_i)_{NU;pq} = \frac{1}{pq} + \binom{pq-i}{pq}.$$

$$\Pr(t_i)_{UC;pq} = \binom{pq-i}{q-1} \div \binom{pq}{q}.$$

$$\Pr(t_i)_{UN;pq} = \frac{1}{pq} + \binom{pq-i}{pq}.$$

$$\Pr(t_i)_{UU;pq} = \frac{1}{pq} + \binom{pq-i}{pq}.$$

Further notes include: i) the identical and uniform distribution of expectancy values for t_i of all entropy-assumption conditions (NN, NU, UN, UU ; pure random assignment of all selections); ii) the similarity of the expressions for partial choice CN, NC , and UC , with NC and UC identical, and CN being identical in structure but exchanging p for q where these appear independently because it is the term for the set size with operative choice (i.e., there are p choices under CN and q choices under NC and UC) and iii) the uniqueness of CU and its mathematical proximity to the entropy-assumption conditions

(not far from NN , NU , UN , UU , only showing substantially better threat-reduction at t_1 , resulting in little threat-reduction power being made available in this design when using a *maximax* decision-making strategy)

4.2. Three-tiered nesting-nested hierarchy:

Arranged by similarly structured ‘families of scenarios’:

Probability of Threat t in position i for Second-Order Scenario XYZ , $\Pr(t_i)_{XYZ}$

Full Choice (one decision structure)

$$\Pr(t_i)_{CCC} = \binom{Ppq - i}{Ppq - 1} \div \binom{Ppq}{Ppq}, \max i = Ppq - (Ppq - 1).$$

Two Choice Nodes, No Trailing Uncertainty (four decision structures)

$$\Pr(t_i)_{CCN} = \binom{Ppq - i}{Pp - 1} \div \binom{Ppq}{Pp}, \max i = Ppq - (Pp - 1).$$

$$\Pr(t_i)_{CNC} = \binom{Ppq - i}{Pq - 1} \div \binom{Ppq}{Pq}, \max i = Ppq - (Pq - 1).$$

$$\Pr(t_i)_{NCC} = \binom{Ppq - i}{pq - 1} \div \binom{Ppq}{pq}, \max i = Ppq - (pq - 1).$$

$$\Pr(t_i)_{UCC} = \binom{Ppq - i}{pq - 1} \div \binom{Ppq}{pq}, \max i = Ppq - (pq - 1).$$

One Choice Node, No Trailing Uncertainty (seven decision structures)

$$\Pr(t_i)_{CNN} = \binom{Ppq - i}{P - 1} \div \binom{Ppq}{P}, \max i = Ppq - (P - 1).$$

$$\Pr(t_i)_{NCN} = \binom{Ppq - i}{p - 1} \div \binom{Ppq}{p}, \max i = Ppq - (p - 1).$$

$$\Pr(t_i)_{UCN} = \binom{Ppq - i}{p - 1} \div \binom{Ppq}{p}, \max i = Ppq - (p - 1).$$

$$\Pr(t_i)_{NNC} = \binom{Ppq - i}{q - 1} \div \binom{Ppq}{q}, \max i = Ppq - (q - 1).$$

$$\Pr(t_i)_{NUC} = \binom{Ppq - i}{q - 1} \div \binom{Ppq}{q}, \max i = Ppq - (q - 1).$$

$$\Pr(t_i)_{UNC} = \binom{Ppq - i}{q - 1} \div \binom{Ppq}{q}, \max i = Ppq - (q - 1).$$

$$\Pr(t_i)_{UUC} = \binom{Ppq - i}{q - 1} \div \binom{Ppq}{q}, \max i = Ppq - (q - 1).$$

Two Choice Nodes, With Trailing Uncertainty (two decision structures)

$$\Pr(t_i)_{CCU} = \binom{Ppq - i}{Ppq - 1} \cdot \binom{Pp - 1}{Ppq - 1} + \frac{q - 1}{(Ppq - 1) \cdot q}, \max i = Ppq.$$

$$\Pr(t_i)_{CUC} = \left[\theta \cdot \frac{Pq}{Ppq} + (1 - \theta) \cdot \left(1 - \frac{Pq}{Ppq} \right) \right] \times \left[\frac{q}{(Ppq - 1)} + \theta \cdot \frac{Ppq - q - 1}{Ppq - 1} \right] \\ \times \prod_{k=3}^{q+1} \frac{Ppq - i - k - \theta + 3}{Ppq - k + 1}, \max i = Ppq - (q - 1);$$

$$\theta = \binom{Ppq - i}{Ppq - 1}, \text{ if } i = 1, \theta = 1, \text{ if } i > 1, \theta = 0.$$

One Choice Node, With Trailing Uncertainty (four decision structures)

$$\Pr(t_i)_{CUN} = \frac{1}{p} \cdot \left[Pp \cdot \frac{(Ppq - Pp)!}{(Ppq - Pp - i + 1)!} \cdot \frac{(Ppq - i)!}{(Ppq)!} + Pp \cdot (p - 1) \right. \\ \left. \cdot \sum_{k=1}^{i-1} \left(\frac{(Ppq - Pp)!}{(Ppq - Pp - k + 1)!} \cdot \frac{(Ppq - k + 1)!}{(Ppq)!} \right) \right],$$

when $i = 1, \dots, Ppq - Pp + 1$; if $i > Ppq - Pp + 1$, $\Pr(t_i) = \Pr(t_{Ppq - Pp + 1})$, $\max t_i = t_{Ppq}$.

If $i = 1$ under CUN, evaluate summation as zero, such that the second term of the addition in the square brackets becomes zero.

$$\Pr(t_i)_{CNU} = \sum_{k=1}^{Pp-P+1} \sum_{i=k}^{Ppq} \frac{1}{q} \left[\frac{(Pp-P)!}{(Pp)!} \cdot \frac{(Pp-k)!}{(Pp-P-k+1)!} \cdot \frac{P}{(Ppq-k)} \cdot \left((q-1) + \binom{Pp-P-i+1}{Pp-P-k+1} \cdot (Ppq-k-q+1) \right) \right], \max t_i = t_{Ppq}.$$

$$\Pr(t_i)_{NCU} = pq \cdot \frac{Pp-p}{Pp} \cdot \frac{(Ppq-pq-1)!}{(Ppq-1)!}.$$

$$\sum_{k=1}^{Ppq-pq+1} \frac{(Ppq-k-1 + \binom{Ppq-i}{Ppq-k})}{(Ppq-pq-k+1)!} \cdot \left((q-1) + \binom{Ppq-i}{Ppq-k} \cdot (2-q) \right), \max t_i = t_{Ppq}.$$

$$\Pr(t_i)_{UCU} = \frac{1}{Pq} \left[\frac{(Ppq-pq)!}{(Ppq-1)!} \cdot \frac{(Ppq-i)!}{(Ppq-pq-i+1)!} + (q-1) \sum_{k=1}^{i-1} \frac{(Ppq-pq)!}{(Ppq-1)!} \cdot \frac{(Ppq-k-1)!}{(Ppq-pq-k+1)!} \right],$$

$$\max k = Ppq - (pq - 1), \max i = Ppq.$$

One Choice Node, With Two Trailing Uncertainties (one equation)

$$\Pr(t_i)_{CUU} = \frac{pq-1}{pq(Ppq-1)} + \binom{Ppq-i}{Ppq-1} \left(\frac{P-1}{Ppq-1} \right), \max i = Ppq.$$

No Choice Nodes (eight equations)

$$\Pr(t_i)_{NNN} = \binom{Ppq - i}{Ppq} + \frac{1}{Ppq}, \max t_i = t_{Ppq}.$$

$$\Pr(t_i)_{NNU} = \binom{Ppq - i}{Ppq} + \frac{1}{Ppq}, \max t_i = t_{Ppq}.$$

$$\Pr(t_i)_{NUN} = \binom{Ppq - i}{Ppq} + \frac{1}{Ppq}, \max t_i = t_{Ppq}.$$

$$\Pr(t_i)_{UNN} = \binom{Ppq - i}{Ppq} + \frac{1}{Ppq}, \max t_i = t_{Ppq}.$$

$$\Pr(t_i)_{NUU} = \binom{Ppq - i}{Ppq} + \frac{1}{Ppq}, \max t_i = t_{Ppq}.$$

$$\Pr(t_i)_{UNU} = \binom{Ppq - i}{Ppq} + \frac{1}{Ppq}, \max t_i = t_{Ppq}.$$

$$\Pr(t_i)_{UUN} = \binom{Ppq - i}{Ppq} + \frac{1}{Ppq}, \max t_i = t_{Ppq}.$$

$$\Pr(t_i)_{UUU} = \binom{Ppq - i}{Ppq} + \frac{1}{Ppq}, \max t_i = t_{Ppq}.$$

Figure Captions

Figure 1: Illustrative Decisional-control Coping Three-Tiered Hierarchy. Bin-sets are construction sites; Bins are job locations nested within construction sites; Elements are jobs of varying threat probabilities of an untoward event (e.g., injury), t_i ; $i = 1, 2, \dots$, Ppq , nested within job locations. This type of diagram is typical of decisional control hierarchy illustrations. In this example, the threat managed via decisional control is the threat of injury occurring during a given task (“job”) in a given area (“location”) of a given building project (“site”) under construction by a given construction company.

Figure 2: Architecture of Decisional-control for Two- (or Three-) Tiered Hierarchy. Notation C stands for free choice regarding associated nesting-hierarchy level; U denotes assignment of an object whose identity is unknown to the decision-maker during the decisional process; N denotes object assignment whose identity is known to the decision-maker from the outset of the decisional process. Notation P stands for number of bin-nesting bin sets; p denotes number of bin-set nested, element-nesting bins; q denotes number of bin-nested elements. Two-tiered hierarchies use only bins p and elements q .

Figure 3: Architecture of Decisional-control Coping for Two- (or Three-) Tiered Hierarchy: Predicting Stressor-Event Occurrences. (see Figure 2 for explanatory notes)

Figure 4: Graphical Depiction of scenario CUN (2,2,2). (See description below graphic)

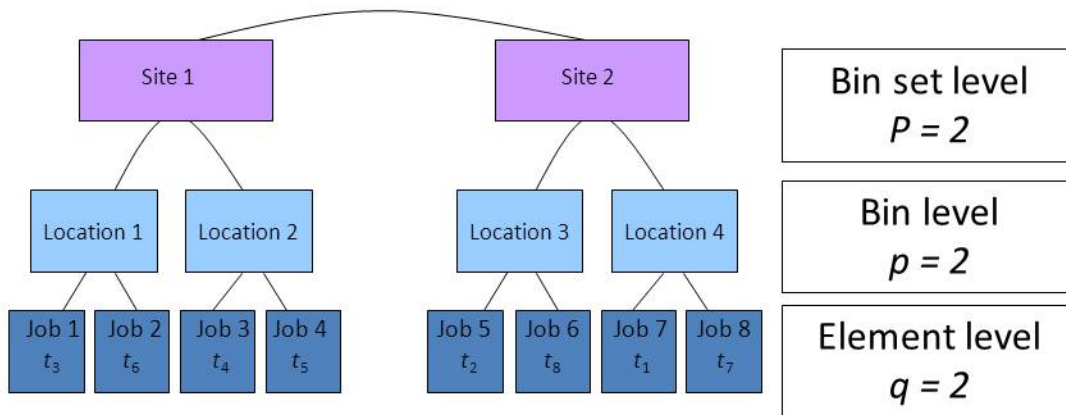
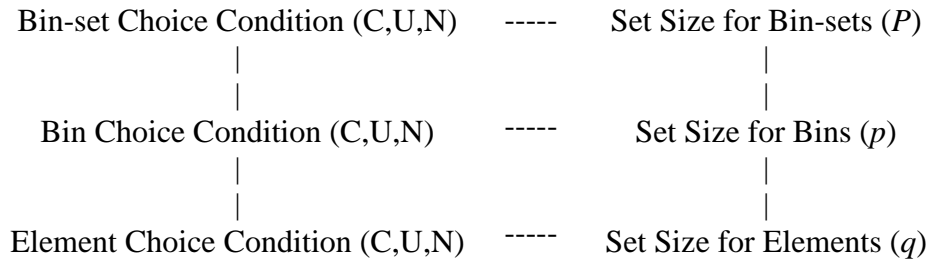


Figure 1

Hyper-parameters
 Structure Conditions $\{C, U, N\}$;
 Condition Parameters $\{P, p, q\}$



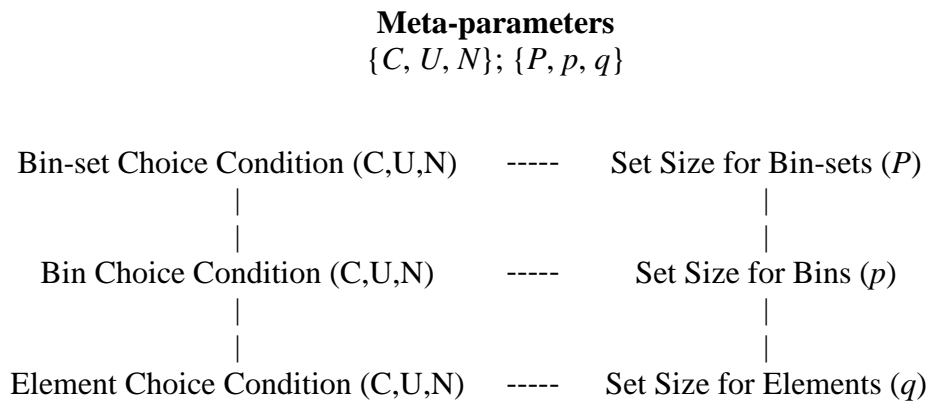
**Base-Distribution Parameters;
 Predicted/Observed variates**

$$Pr(t_i);$$

$$t_i, i = 1, 2, \dots, (P)pq.$$

$$\text{Cumulative Expectation of Threat } E(t) = \sum_{i=1}^{(P)pq} Pr(t_i) \cdot t_i$$

Figure 2



**Hyper-Parameters;
Base-Distribution Parameters**

$$Pr(t_i);$$

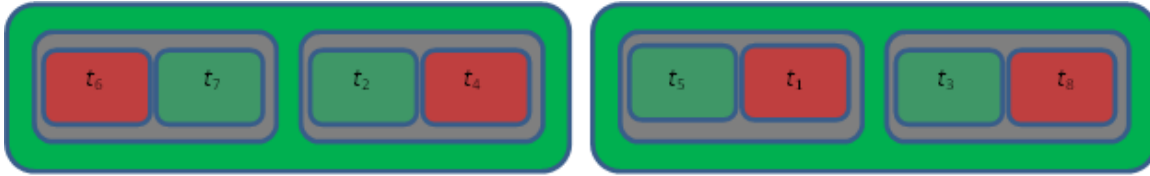
$$t_i, i = 1, 2, \dots, (P)pq.$$

Conditional Expectation of Threat $E(t) = t_i$ for a given obtained value of i .

Predicted/Observed Variates

$$m \in \{0, 1\}; Pr(m=1) = t_i.$$

Figure 3



Graphical Description of $Z_{CUN(2,2,2)}$: Two bin-sets ($P = 2$) with choice condition “C” (coloured green), two bins ($p = 2$) per bin-set with choice condition “U” (coloured grey), two elements per bin ($q = 2$) with one element per bin (one element coloured green, excluded elements in red). Threat values t_i are interspersed to depict random distribution of t_i values among elements nested in bins, and bins nested in bin-sets. The probability of obtaining t_i is a function of access or obstruction to t_1, t_2, t_3, \dots in preferential order. In this decision scenario, a decision-maker would select the left-hand bin-set. This bin contains t_2 , and is the hope of the decision-maker when the left-hand bin-set is selected using the only available decision-making power, bin-set choice ‘C’. Other cognitive evaluations, under what is called ‘Outcome Set Size’ (*OSS*), would consider *possible other element encounters*, other possible final outcomes in terms of t values. In this case, t_7 is also possible in the same bin-set, and t_5 and t_3 are also available in the right-hand bin-set. As such $OSS = 4$; in *CUN* more formally, $OSS = Pp$, the product of ‘C’- and ‘U’-node set sizes.

Figure 4

2.3 Comment: “Towards a Comprehensive Model (...)”

The foregoing manuscript is somewhat abstruse. However, it presents what could be a workable foundation for further integration of decisional control modeling with outcome-oriented stress research. Stress can tenably be conceived of as driven by the obtaining of a desirable objective (a ‘positive’ goal) or the avoidance of a known peril (a ‘negative’ goal). Consequently, the understanding of how to shift the probabilities for successful goal pursuit in one’s favour through nested decision-making becomes highly relevant.

Having a functional structure (the mixture-model in the preceding manuscript) in which to place decisional-situation features provides the advantage of placing many types of situations on a comparable footing. Situational features such as number of alternatives (P, p, q), information availability (C, N : yes; U : no) and executive power (C : yes; U, N : no) at different levels of decision-making are common in organized human social life.

Companies, families, charities, schools, armed forces (police, military), and bureaucracies generally all apportion authority somewhat systematically and hierarchically. This, not to mention the valuable footing provided to researchers who would seek to systematically vary these quantities in a cohesive, unified, formal manner.

The sequential linking of probabilities described in the preceding manuscript starts at the most basic phenomenological level: occurrence or non-occurrence of an event (either of which may be the desired outcome). Over this most common starting point for any type of data, simply counting ‘yes’ or ‘no’, are mounted threat values t_i – the chance of a ‘yes’. Governing threat values, in turn, are the chance of obtaining the threat value in ordinal (aka “ranked”) position i , where $i = 1$ is best and i at a maximum value is worst. This level of ‘probability governance’ is denoted $Pr(t_i)$, the chance of getting t_i .

Governing $Pr(t_i)$ in turn again, is the probability of a given decision structure, such as CC, NC, CU, or in a three-level hierarchy, CNU or UUN, for example. To index these decision structures, the indexing variable j is recruited, similar to i for threat.¹ That is,

¹ Note that a ‘choice structure’ refers strictly to the node-by-node pattern of choice condition (C, U, or N) at each hierarchy level (bin-sets (if applicable), bins, and elements). A ‘decision structure’ refers to the

what i is to threat, j is to decision structure. One difference is that j does not refer to an ordinal position of decision structure. There is no preferential ‘rank’, though this could be done. Rather, j is properly a nominal variable. Nonetheless, each decision structure can be identified, and an expectancy count of structure frequencies can be developed or estimated based on counting the number of occasions when the particular node and parameter configurations combine to produce a decision structure. Because $Pr(t_i)$ can now be completely codified and located as a known distribution of probabilities within the set of decisional-control decision structures, $Pr(j)$ is the likelihood of a particular *distribution* $Pr(t_i)j$, characteristic of given decision structure j , being operative. As an example, our initial work on distribution of decision structures assumed a ‘gentle prior’ (‘mild assumption’) of equal likelihood for all nine first-order scenarios (see p. 38). This meant a 1/9 chance of one of CC ($j = 1$), CN ($j = 2$), CU (...), NC, NN, NU, UC, UN, and UU ($j = 9$) determining relative access to the set of t_i values for the decision-maker.

The assortment of j decision structures can itself be considered governed by the availability of choice conditions (C, U, and N) and the set sizes at each choice node (P , as applicable, and p and q). These model parameters can be conceived of as being potentially in short or uneven supply, hence benefitting from prudent administration. Allotment of choice to a subordinate node may be costly to a super-ordinate decision-making unit, if overarching concerns are not being met or system-wide considerations become difficult to address. This may especially be true if error-free ‘maximax’ decision-making (selecting to obtain the best) is not occurring at subordinate nodes. Conversely, subordinate decision-makers may find their super-ordinate decision-makers make *more* errors in their decision-making than subordinate agents. The rise of tyranny (removal of subordinate freedom) and groundswells of social upheaval (toppling of corrupt regimes) might well be influenced by comparative decision-making efficacy.

combination of choice conditions by node and a parameter set size values (P (if applicable), p , and q). A ‘decision scenario’ is the expression used to refer to a particular arrangement of choice conditions and set sizes, such as CUN(4,2,3).

In sum, the capacity to expect and produce desired outcomes has been housed within five ‘levels of governance’ as modeled and distributed statistical quantities: event outcome ($m = 0,1$), event probability ($Pr(m = 1) = t_i$), access to event probability ($Pr(i)$ for $Pr(t_i)$), likelihood of a given access to event probability ($Pr(j)$ for a given $Pr(t_i)_j$), and the availability of decisional control parameters C, U, N, and (P), p , and q for creating the distribution J of decision scenarios $Z_{C,U,N;(P),p,q}$ each with an indexing identity denoted specifically with the label of lower-case j . This general distribution J then provides the context for relative frequency of a given decision structure j , with decision structure j governing a probability distribution $Pr(t_i)$. Discrete probability distribution $Pr(t_i)$ in turn allots the chance of obtaining a good event probability t_i , and a favourable t_i hopefully allows better-than-random chance of event non-occurrence (in the case of threat), or of event occurrence (in the case of a desired outcome).

3 A Dynamic Catalog of Decisional Control Values

3.1 Introduction to the Third Component Document

The third document within the full dissertation is a catalog of decisional control values for consultation by researchers and others interested in using a decisional control approach. These tables are created to be user-friendly while also maintaining a transparency that is intended both for pedagogical purposes, to train and teach others in model specifics, and for construct validity, allowing the inspection of the algorithms generating probability distributions. These spreadsheets are proffered as a component document in their own right within the dissertation, as they can generate full ranges of decisional control probability values for the 283 different permutations of p and q values that produce a product of 100 or less (i.e., $pq \leq 100$; $p, q > 1$; $p, q \in \mathbb{N}$) and the 324 different permutation of P, p, q values with analogous constraints (i.e., $Ppq \leq 100$; $P, p, q < 1$; $P, p, q \in \mathbb{N}$). In practice, this means the most extreme values for p and q in first-order choice structures are $(p, q) = (2, 50)$ or $(50, 2)$ and the most even is $(p, q) = (10, 10)$, with the lowest being $(p, q) = (2, 2)$. For second-order structures, the most extreme and most even are $(P, p, q) = (2, 2, 25)$, $(2, 25, 2)$, or $(25, 2, 2)$ and $(5, 5, 4)$, $(5, 4, 5)$, or $(4, 5, 5)$; the lowest set of values is $(P, p, q) = (2, 2, 2)$.

The value of this document is comparable to a more historic form of tabulation for consultation values, a catalog, as for z -values, t -values, logarithmic tables and other relevant statistical quantities. In the older style ‘look-up table’ catalogs (before the advent of rapidly accessible programming and computation, as used in this study) it might be reasonable in the case of a ‘decisional control value catalog’ to expect one full page to list a comprehensive set of values for a given choice structure and specific set of parameters. On such a page, a given set of $Pr(t_i)$ values, adjusted t_i standardized vector, and resultant $E(t)$ values per element index number (i) and in some cases, per leading-bin number (k), as well as their overall summation might be listed for consultation.

In a liberal estimate, the dynamic and interactive spreadsheets are able to generate the equivalent of 283 x 10 pages (including Main page), or 2,830 individual table pages for the first-order scenarios and 324 x 28, or 9,072 pages of independently valid decisional

control values information. By a more conservative estimate, condensing for equivalent pages (where the calculations are the same), there would still be 283 x 6 pages (Main plus 5 subsets of functionally equivalent choice structures: CC, CN, NC/UC, CU, NN/NU/UN/UU) or 1,698 pages in the first-order consultation tables catalog. For the second-order consultation tables, a total of 324 x 16 pages (Main plus 15 subsets of functionally equivalent choice structures: CCC, CCN, CNC, NCC/UCC, CNN, NCN/UCN, NNC/NUC/UNC/UUC, CCU, CUC, CUN, CNU, NCU, UCU, CUU, NNN/NNU/NUU/UNN/UNU/UUN/UUU) or 5,184 pages of unique information would validly be printed. My intent with this third ‘document’ is to provide a comprehensive reference guide for the allocation of probabilities in hierarchical, partially-obstructed choice scenarios through the tutorial below and the online accessibility of the dynamic, interactive consultation tables.

3.2 Decisional Control Values: Catalog Tutorial

Two main files are composed in the Microsoft Excel 2010 spreadsheet program, one each for two-level (‘first-order’) and for three-level (‘second-order’) hierarchies. The first order file has ten worksheets, accessible via the tabs at the bottom of the program screen. These consist of a Main worksheet to coordinate the file, and nine worksheets, each named for a choice structure (CC, CN, CU, NC, NN, NU, UC, UN, UU). These are called ‘choice structure’ here, because the parameters, namely, p bins and q elements-per-bin are to be inputted by the user. In just moments of calculation, the spreadsheet updates a given set of probabilities of access to a given threat value $Pr(t_i)$, and combines them with a set vector of t_i values, with the value of i ranging from 1 to pq (p times q). In some choice structures, the probability of accessing a given t_i becomes true zero (as opposed to infinitesimal, in some other cases) and hence the product of $Pr(t_i)$ and t_i is zero. For all nine choice structure worksheets, a mathematical expectation of threat, also known as the cumulative expectation of threat or again threat expectation $E(t)$ is calculated by summing the product of $Pr(t_i)$ and t_i across all values of i . As such, each worksheet yields a ‘threat expectation’ that is both proper to the choice structure *and* to the parameters that the user has entered. In terms of usefulness, the model allows assessment of the threat

level inherent in the decisional control scenario examined, accounting for both choice and number of options. The second-order spreadsheet has the same design.

Basic usage for the first-order spreadsheet will be described here, and is applicable to the second-order spreadsheet, also. Consulting the decisional control values tables involves the inputting of the p and q parameter values (minimum single value of 2, maximum combined product value of 100) in cells B5 and B6, in the appropriate worksheet. If a combined $E(t)$ is desired across choice structures with a constant p and q , the constituent $E(t)$ values can be pooled on the Main page.

The tables are designed to follow a convention, with choice structure identified at the top left (cell A1). The choice structure is also the name of the given worksheet, accessible by clicking its specific tab at the bottom left of a Microsoft Excel 2010 spreadsheet display. Below the choice structure name at cell A1, a simple description in a few lines of characteristic features of this choice structure, and the p , q , and pq values. Only the p and q values need be entered, the formula-based dynamic nature of the spreadsheets does the other calculations upon the p and q values being entered definitively with the press of the “Enter” key, or movement to other cells with the Tab key, arrow keys (up, left, down, right) or by clicking on another cell with the mouse.

Visible immediately to the user is the label $E(t)_{\text{norm}}$ in cell D7, and its numerical value in cell E7, adjacent. This value is the cumulative expectation of threat in the decision scenario entered, the combination of a specific choice structure (e.g. ‘CU’) with a specific pair of parameters (p , q). The subscript ‘norm’ is used to denote ‘normative’, indicating that the list of t values used is the normative vector that divides the full range of probability from zero to one into pq different, evenly spaced values, with an increment of $1/pq$. Using the number line convention, t_1 and t_{pq} are at the start and end of this range of t values, respectively, and are themselves placed at an interval of half the standard increment (a distance of $1 / (2pq)$) to the right of 0 (for t_1) and to the left of 1 (for t_{pq}). This approach creates a balanced vector, whereby choice structures without the threat-reducing element of choice produce $E(t)_{\text{norm}} = 0.5$. Values for $E(t)_{\text{norm}}$ less than 0.5 indicate the threat reduction available through decisional control.

An example with $(p, q) = (2, 4)$ and values for $E(t)_{\text{norm}}$ is reported in Table 1 below:

Table 1

Decisional Control Values Across Choice Structure for Parameter Values $(p, q) = (2, 4)$

	p	q	$Pr(t_1)$	$E(t)_{\text{norm}}$
<i>CC</i>	2	4	1.000	0.0625
<i>CN</i>	2	4	0.250	0.3125
<i>CU</i>	2	4	0.250	0.4375
<i>NC</i>	2	4	0.500	0.1625
<i>NN</i>	2	4	0.125	0.5000
<i>NU</i>	2	4	0.125	0.5000
<i>UC</i>	2	4	0.500	0.1625
<i>UN</i>	2	4	0.125	0.5000
<i>UU</i>	2	4	0.125	0.5000

Commenting on Table 1, above, $CC(2,4)$ provides the most threat reduction. This is model-consistent, in that the best available option, in this case $1/(2pq)$ to the right of zero on the standard threat vector can always be selected directly. In other words there is a 100% chance of the best threat value option available, as reflected in the $Pr(t_1)$ column value for CC of 1.000. Note, a convention for $E(t)$ values is to use four decimal points; for $Pr(t_i)$ values, three decimal points are used in order to distinguish these two types of probabilities. The next most favorable decision scenario is $NC/UC(2,4)$, wherein having four options at the element level allows considerable threat reduction because the choice available is also at the element level (i.e., in NC/UC). For NC and UC , which are functionally equivalent in this context, the ‘C’ choice condition is at the element-level node, allowing selection among q elements, or more centrally to the operative mechanism in decisional control, *elimination of the $q - 1$ least desirable elements*. The $CN(2,4)$ scenario provides the next most threat reduction, at $E(t)_{\text{norm}} = .3125$. Note that this is just about double the threat expectation in the $NC/UC(2,4)$ scenario, where $E(t)_{\text{norm}} = .1625$. Interestingly, a quick check with the interactive tables confirms what is deducible by their complementary analytical formulations, that the $E(t)_{\text{norm}}$ values would be swapped, exactly, should the parameters be switched to $(p, q) = (4, 2)$. This is directly due to the

relative placement of the ‘C’ choice condition node (for bins in CN and for elements in NC/UC). The leverage in reducing threat expectation is a function of increasing parameter value at the node where the ‘C’ choice condition is operative.

Two more choice structure-types can be highlighted from Table 1, CU and NN/NU/UN/UU or simply the NN-family. The CU choice structure has been shown to be only slightly better than the completely randomly assigned NN family of values. This finding was reported from extensive simulation work (Shanahan, 2007; Shanahan & Neufeld, 2010). The discrete distribution in the CU structure is such that $Pr(t_1)$ is identical to $Pr(t_1)$ for CN, but subsequently, all remaining values have a uniform distribution such that for $Pr(t_2)$ to $Pr(t_{pq})$, using a secondary index $i' = 2, 3, \dots, pq$:

$$Pr(t_{i'}) = \frac{q - 1}{q} \cdot \frac{1}{pq - 1}$$

In the case of CU(2,4), this evaluates to $3/4 \times 1/7$, or $3/28$, or 0.107. The flatness (equal probabilities from $i = 2$ upwards) and length (up to and including $i = pq$) of this distribution of probability of obtaining t_i under a CU choice structure means it is exposed to the highest threat vector values (i.e., t_{pq} , t_{pq-1} , t_{pq-2}) in generating the product value of $Pr(t_i) \cdot t_i = E(t)$. Compared to the probabilities for its one-‘C’ compatriot, CN, the chances of obtaining $Pr(t_2)$ under CU (a great option if it can be obtained), is comparatively lower (CU, 0.107; CN, 0.214) and $Pr(t_{pq})$ is higher (CU, 0.107; CN, 0.000 – true zero). Note that this is a trend that holds, without contradiction, in the range of t values between $Pr(t_2)$ and $Pr(t_{pq})$, also. Because of this, the functional equivalence that is seen for NC and UC, whereby calculations of $E(t)$ use the same formula for both choice structures, is *not seen* for CN and CU. These latter two are distinct and CN will always have the advantage; on $Pr(t_1)$, they are equal, and CN will always exercise more threat-reduction power at subsequent indexing values i for threat values.

One final feature that is of particular interest in the cases of CN and NC/UC, is the reaching of true zero probability at some value of $i < pq$. This occurs because the exercise of decisional control at the choice node in these choice structures always occurs with some ability to eliminate the worst threat option(s). Specifically, $p-1$ of the worst options,

counting back from t_{pq} , are removed from possibility by the CN choice structure, and similarly the $q-1$ worst options, counting back from t_{pq} , are removed from contention by the NC/UC choice structures. If the magnitude of the threatened event is considerable, eliminating the worst threat levels can be very powerful, especially if threat increments are not equally spaced. Poignantly, ordinal position i still retains the same probability of being obtained by the decision-maker, regardless of t value increment. If the list of threat elements contains threats such as permanent injury or disability in the last positions, elimination of the worst few in a list of threat possibilities because they are ordinal positions in a decisional control structure becomes a noteworthy advantage. It is possible under CN and NC/UC to eliminate, with theoretical certitude, the $p-1$ and $q-1$ worst options, respectively, according to ordinal position (assuming error-free selection). By contrast, it is not possible to eliminate any t_i values under the CU choice structure.

This is a sample of what is available by consulting the dynamic tables in concert with the analytical formulae available in the Appendix of the second component document. These decisional control value tables will be available upon request at the candidate's website publish.uwo.ca/~mshana, and can be consulted more extensively if desired.

3.3 Comment: "A Dynamic Catalog (...)"

As a manuscript *per se* has not been inserted, the closing comment will be brief.

The essential structure for a threat-based decisional control model application is an ordinal sequence of likelihood values (threat values) for an undesirable 'state of affairs', or outcome. In some sense, every clinically-oriented research subfield can be said to have an ordering of more or less desirable situations, or an ordinal progression of likelihood of a specific undesirable situation such as adolescent substance abuse, PTSD intrusive symptoms, and act of alcohol-related aggression, non-adherence to a medication regimen, or a triggered phobia. As such, the example of an exposure hierarchy in the treatment of phobias can serve as a starting point for potential utility of the model.

In an exposure hierarchy, clients with a particular phobia list in increasing order various stimuli they might encounter that will progressively (ordinal positioning) trigger more

fear, by their estimation. For a fear of snakes, for example, this might range from thinking of a tube at 10 % of maximal fear, through thinking of a snake at 30 %, through seeing a hose in the grass at 50 %, through being in the room with a snake at 70 %. The feature emphasized in this context is the *ordinal positioning of threat*. In the decisional control model approach threat can be managed, by contradistinction with the exposure method where exposure to the threat is the therapeutic element. Nonetheless, a possible hybrid therapy might be considered, whereby four, six, eight, or other even-numbered multiple of threat possibilities could be actively *managed* by the clinical patient, but where the two-level hierarchy decision structure could be set by the clinician. For example, in Week 1, simply seeing the four threat options and navigating easily to a 10 % fear item (subjective units of distress) could be possible, and confer initial empowerment, under a Choice-Choice structure. Week 2 might see the use of a CN structure; Week 3, NC, and so forth so that over perhaps 8 or 9 weeks of treatment, most choice structures would be encountered. By the last several weeks, a much more random exposure to *level of feared stimulus* would occur, including an Uncertainty component (at least one U node). This would gain increased ecological validity as well as inuring the client to the possibility of the highest perceived threat in list with an even-number of items (e.g., 70 % of maximal fear for 'being in the room with a snake', at the highest position). In a similar way, decision-making by the individual can be supported, constrained, and ultimately retrained according to decision structures based on the operation of decisional control. This can conceivably be applied with any type of clinically-oriented intervention where there is a threat to be mitigated or responsibly managed, and a known ordinal progression in situations that raise or lower that threat.

There are considerable potentialities for investigation, exploration, and mathematical enjoyment in the tables published, as outlined above. They are designed to make the involved calculations within the decisional-control approach more user-friendly, but also transparent for the motivated reader, interested investigator, and theoretical researcher. Their availability can be compared to that of a 'pocket calculator for decisional control research'. From a higher vantage point, they consist of essentially a new type and pattern of discrete distributions that, to the knowledge of this researcher, are not charted elsewhere in the main body of the sciences.

4 « Information Processing for Threat Reduction in Decisional Control Scenarios »

4.1 Introduction to the Fourth Component Document

Soon after its original proposal and design (Neufeld, 1982), experimental testing and verification of the decisional control model has been an important component of this decidedly theoretical approach (Kukde & Neufeld, 1994; Morrison, Neufeld, & Lefebvre, 1988). The study presented as the fourth component document for this dissertation entitled “Mathematical modeling of Stress Management via Decisional Control” is a novel, extensive application of the paradigm using a broader range of measurement modalities: psychophysiological, reaction time, and subjective stress ratings.

Additionally, the theory anchored in the model structure has been expanded using abductive reasoning, described in the first component document, “Clinical Mathematical Psychology”, in order to create a theoretical basis for past and future empirical findings.

Also notable in this study, “Information Processing for Threat Reduction in Decisional Control Scenarios”, is the recruitment and application of advanced personality and individual differences work on decision-making preference. This work, the composition of a ‘Maximizing Continuum’ derived from model based choice-preference parameters, is briefly described in this study but more extensively elsewhere (Shanahan, Pawluk, Hong, & Neufeld, 2012; see References section within the integrated fourth manuscript, below). This study will be submitted for publication, pending the completion of its function as the fourth study within this dissertation.

4.2 “Information Processing for Threat Reduction (...)”

The manuscript “Information Processing for Threat Reduction (...)” is inserted in Microsoft Word 2010 format below. It comprises 72 pages as an independent manuscript, and 81 pages within Chapter 4, pages 76-156 of this dissertation document.

Information Processing for Threat-Reduction in Decisional Control Scenarios

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Abstract

Formal modeling of decisional control outlines an ‘economy’ for negotiating stress: information processing is provided in order to receive threat reduction (cf., Morrison, Neufeld, & Lefebvre, 1988). Participants ($N = 65$) made selections for the best available (lowest) threat-options in response to vignettes evoking the stress of physical danger or social evaluation. A 3 x 2 factorial MANOVA used three levels of Choice Structure (full choice, constrained choice, no choice) in a two-tier hierarchy, with two levels of Element Set Size (number of choices). Dependent measures were maximum heart rate, minimum heart rate, vascular resistance, duration of decision-making cognition, and subjective stress ratings. Results lend empirical support to a main effect of Choice Structure, a main effect of Element Set Size, and their interaction. The Choice Structure main effect suggests that participants tend significantly toward the intermediate Choice Structure (constrained choice) for allocation of increased information intake (lowest minimum heart rate), longest time of decision-making cognition, and report the highest stress levels (suggesting increased effort). By contrast, the full choice and no choice experimental levels did not differ significantly from each other on these measures. The Element Set Size main effect was characterized similarly by increased information intake (lower minimum heart rate), longer time of cognition, and higher subjective stress ratings at the experimental level with fewer choices (two sets of two choices) rather than more choices (two sets of four choices). The interaction involves a more pronounced difference between the full choice and constrained choice levels when there are more choices than when there are fewer. A mechanism is proposed explaining ‘preference for the intermediate’ with equivalent and counterbalancing valuation of information processing provided per threat-unit faced in the decisional scenario, and threat-exposure accepted per unit of control afforded by the decisional scenario. A measure of ‘decision value’ is thus obtained theoretically. This theoretical index of decision value predicts minimum heart rate (pseudo- $R^2 = .92$), time of decision-making (pseudo- $R^2 = .72$), and subjective stress ratings (pseudo- $R^2 = .77$) across the 3 x 2 experimental condition cell averages.

Keywords: decisional control, threat reduction, information processing, stress and coping.

The cultivation of good decision-making patterns is highly relevant in an age of proliferating information (cf. Levitin, 2014; Miller, 2009). Abundance of information makes necessary the improvement of the human decision-maker for evaluating, selecting, and implementing responses in situations of potential gain or loss. Charting the features of such situations systematically can be a valuable aid to decision-makers and applied decision science.

In this study, we use psychophysiological indices of stress (e.g., Kukde & Neufeld, 1994; Tomaka, Blascovich, Kibler, & Ernst, 1997), reaction time measures specific to the decision-making process, and subjective stress ratings as arbiters of participant sensitivity to the decision features of choice constraint and number of choices. These decision features are varied systematically within a formal model of decisional control, a cognition-intensive form of coping (Neufeld, 1982; Morrison, Neufeld, & Lefebvre, 1988; Shanahan & Neufeld, 2010). Psychometric measurement in decision-making preference, anxiety, and response to uncertainty adds an individual differences context to behavioral observations.

Decisional Control: Research Paradigm and Experimental Platform

The model used in the present study is a formal model of decisional control. Working on the assumption of ‘opting for the best’ (“*maximax*”, defined below) the model facilitates the apprehension of plausible and straightforward considerations that are relevant to a decision-maker. Choice constraint (freedom of selection) and number of choices (possible selections to evaluate) are varied within the theoretical and experimental structure of the study. With this range of choice scenarios, we examine psychophysiological fluctuations, time spent on decision-making, and subjective stress

reports under simulated stressful decision-making conditions, through the lens of decisional control concepts. An illustration is presented immediately below.

Decisional Control Illustration: ‘Planning a Picnic’

The decisional control model is characterized by the assumption of the decision-maker’s knowledge of an array of probabilistic threat levels, one of which must be engaged to complete the scenario. As a pleasant and accessible example, planning a company picnic with the threat of inclement weather can be approached through the lens of decisional control.

Planning a picnic – example structure.

In order to illustrate decisional control concepts, the picnic planning will be explained in parallel with the decisional control concepts involved at each stage. The fundamental requirement of a decisional control approach is a known array of probabilistic threats. As such, this example invokes the modern availability of a daily probability of precipitation (P.O.P.) as the defining threat facing a picnic. No other threats are accounted for in this illustration. Nonetheless, if a rank-order list of ‘combined threat’ was developed from the additive nature of other threats (food available, guests available, competing events, lack of venue), a decisional control approach can be used for any rank-ordered list of probabilistic threat values, with success being defined as avoidance of the probabilistically threatened outcome.

For the sake of illustration, we assume there is a four-day period (such as a long weekend) during which a day-long company picnic may be held. We can use the daily P.O.P. as the ‘index of threat values’, the list of potential occurrence likelihoods of what is generically defined as an ‘untoward event’ in decisional control literature (e.g.,

Morrison, Neufeld, & Lefebvre, 1988). In this example, the list of threat probabilities is the rank-ordered list of probabilities that it will rain on a given day in the eligible four-day period.

We will assume that any rain will be ‘untoward’ for the success of a picnic. A ‘vector’ of probabilities of precipitation P.O.P. is laid out in Table 1, over a four-day meteorological prediction period. What is also represented is the ordinal position of each day’s P.O.P., the practical ‘threat value’ in this example, as an index from t_1 as the lowest chance of rain and t_4 as the highest threat value, or highest probability of precipitation.²

Table 1

Probability of Precipitation as Threat Values over a Four-Day Long Weekend

	Friday	Saturday	Sunday	Monday
Probability of precipitation <i>P.O.P.</i>	40%	30%	70%	10%
Ordinal Threat Value t_i	t_3	t_2	t_4	t_1

For a decisional control approach, we subdivide the set of four possible picnicking days into two portions: “earlier in the long weekend” (Friday or Saturday) and “later in the long weekend” (Sunday or Monday). This creates *two sets of two choices*, a structure that mirrors one of the two experimental levels in this study for number of choices. For generality, mathematical work on this model uses the terms two ‘bins’ in

² Previous work with the model has stipulated a requirement of equal increments between threat values (the difference between each threat value and its ordinal neighbor(s) set as a constant; Shanahan & Neufeld, 2010). Recent developments, however, allow for complete model functionality with only an unequivocal *ordinal* ranking of threat values, where equal increments are not necessary (Shanahan, Nguyen & Neufeld, 2012).

each of which two ‘elements’ are *nested*. The other experimental level in the present study has *two sets of four choices*, referred to more formally as two bins in each of which four elements are nested.

Within the two divisions of “earlier in the weekend” and “later in the weekend”, two threat values are nested (see Figure 1.1 for a structural depiction). The utility of the decisional control model comes into play now in this way: if this situation arose, for statistical argument, 10,000 times (a very large number approximating distribution patterns unlikely to change with increased sample size), what statistical advantages would choice of a) portion of the weekend, and b) day within the selected portion confer on the picnic planner as improved odds of a successful event (no rain)?

Figure 1.1 Decisional Control Hierarchy with Bins and Elements

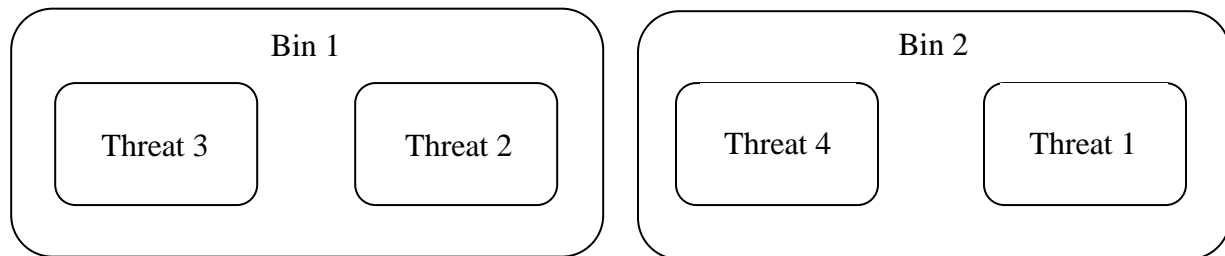


Figure 1.1. Depiction of two bins, each nesting two elements. In the picnic example, Bin 1 is “early in the long weekend”, Friday is Threat 3, Saturday is Threat 2. Bin 2 is “later in the long weekend”; Sunday is Threat 4 and Monday is Threat 1, the lowest P.O.P.

Planning a picnic – explanation of Cc, Nc, and Nn structures.

If the planning committee is given free choice of portion of the weekend, and free choice of day within that portion, then they can choose the lowest P.O.P. every time (whether each year, each occasion, or every hypothetical occasion) for the company

picnic. If this is feasible, it is clearly the best situation. In the example values from Table 1, the picnic would be set on the Monday, with a 10% probability of precipitation. More powerfully, if company policy was such that organizers could always select the weekend portion (early or late) of the annual company long-weekend picnic and could select a specific day within that portion, then, banking on the meteorological predictions every time, they could always select the day with the lowest chance of rain in a four-day weekend. This doesn't mean just Monday, it means an 'always' chance of obtaining t_1 , the best option or lowest threat of rain in the four-day forecast. In the parlance of the decisional control model this is a Choice-Choice structure denoted Cc , whereby there is choice of bin and choice of element within a chosen bin.

There may be difficulty, however, in ensuring that employees keep all four days of their long weekend open until reliable weather reports are issued. As such, a more feasible arrangement may be to determine by a brief survey whether employees at a given branch of a company prefer to keep the earlier or later portion of the long weekend available. Then, within the two-day window, a lowest P.O.P. day can be selected. This is a No Choice-Choice scenario for the planners, denoted Nc . There is external assignment of bin for the planners by employee preference (only keeping either the earlier or later two-day portion of the long weekend available), but choice of element for the planners (either of two days in that portion is available). The advantage here is that, for example, the organizers will never need to hold the event on the *worst* P.O.P. day. They will always be able to choose one of t_1 , t_2 , or t_3 and never be forced to accept t_4 . In fact, to highlight the advantage, we can assume that the P.O.P. allotments are random (threat values for rainy days over the four-day weekends), and that the portion of the weekend

reserved is free to vary also, year-to-year. If this approach to company picnics, as a policy, holds across 100 branches nationwide, and over hypothetically 100 years of celebratory company picnics (10,000 events), a precise guess (mathematical-combinatoric estimation) of the number of times that planners were able to select the best, second-best, or third-best weather day for P.O.P. is half the time, one third of the time, and one sixth of the time, respectively.

The logic in the proportions for t_1 , t_2 , and t_3 is that under random assignment of weather patterns, there is a one-in-two (three of six total combinations of two groups of two from a full set of four) chance that t_1 will be in the two-day-weekend portion that planners have available. There is a one-in-three (two of six combinations) chance that t_2 will be in the available two-day portion and that t_1 simultaneously is not in that portion, and a one-in-six (one of six combinations) chance that the two-day portion contains t_3 and t_4 . In this latter case, t_3 will be selected, never t_4 . The worst or, in this case, fourth-best choice need never be selected, representing a zero probability of having to organize a picnic on the day with the highest chance of rain.

The final scenario relevant for the present experimental report involves the company celebration picnic day being directly chosen by the most senior person being celebrated. This person or group of persons, perhaps new retirees or celebrating birthdays, may include weather, friends, or any number of considerations, but the planners will have no influence on choosing of the day with P.O.P. in mind. The only useful estimate for P.O.P. over the four-day period is the average across the four days of the long weekend. Despite this estimate, actual selection by P.O.P. is out of the planners' hands. From the planners' point of view, this represents a No Choice – No Choice

scenario, labeled an Nn structure, where there is a one-in-four chance for each of t_1 , t_2 , t_3 , or t_4 , falling on the picnic day, equal likelihood from best to fourth-best P.O.P.

Planning a picnic – model implications and applications.

Though fairly innocuous, this example is meant as an illustration to facilitate exposition. Situations where a maximax approach applies include stress-charged environments such as air-traffic control, pilot decision-making, SWAT team deployment, and other high-stakes, decision-making contexts requiring rapid, effective heuristics and algorithms for optimal outcomes. The value of the formal model is that it is the structure itself that is understood, where statistical comparison of full choice, constrained choice, or lack of choice among a known set of probabilities is valuable.

As a hypothetical application of this understanding, Company Z can establish a picnic policy in keeping with best chance of success and local culture and circumstance. The company might establish an Nn structure at its branch in Arizona, where P.O.P. (usually low) is generally in favour of a successful picnic, and there may be a higher proportion of senior staff with power to request a specific day. There may be profit to using an Nc structure in Ohio, where there is rain often enough, but family-minded values discourage encroachment on family time (an Nc structure means a two-day rather than four-day window is to be kept available). In Seattle, a Cc structure for company picnics would likely suit the purpose best, where rain is frequent, the workforce is younger, and a culture of competitive bonuses can make up for infringement on employee freedom in requesting them to reserve a four-day window.

Planning a picnic: Archival analysis.

An archival analysis of this technique was performed by retrieving daily weather reports from a local international airport (London, Ontario, Canada). Using actual precipitation readings (<http://climate.weather.gc.ca>) in the context where P.O.P. is used hypothetically above, the *Cc*, *Nc*, and *Nn* decision structures can be tested for retrospective selections of good picnic days. A tie-break ordinal ranking for multiple zero precipitation days was absolute distance to a set ideal temperature of 25°C. Over 10 four-day periods (the 9th to the 12th of each month) for warmer months between August 2013 and May 2015, the actual average result across the 10 selected picnic days for precipitation and temperature are: 0.02 mm and 22.4°C under the *Cc* model, 2.10 mm and 21.5°C under the *Nc* model, and 8.92 mm and 20.8°C under the *Nn* model. External assignment for *Nc* bin and for *Nn* bin and element-within-bin was done with a randomization function in a common spreadsheet program, whereas decision-maker selection in *Cc* and *Nc* opted for the best available bin and element, and element-within-assigned-bin, respectively. The difference in the *Cc*, *Nc*, and *Nn* results in a sample of ten real-world occasions obtained within the same ten four-day ranges illustrates clearly the anticipated relative advantages of full choice, constrained or partial choice, and single-item choice over identical ranges of selection interest.

This same logic for the relative merits of decision structures holds generally for scenarios where there is I) nested decision-making, II) a clear rank-order of threat values, and III) the potential for a full set of choices, partial set of choices, or single choice available within a nested decision structure. As such, the investigations herein are made to evaluate stress as a function of the decision-maker's ability to select a less threatening

option by having and evaluating options to a greater or lesser degree. Obtaining the best possible outcome is the goal, by lowering the likelihood of the ‘untoward event’. This threat-mitigation impetus for the decision-maker is the focus of the threat-management approach to stress that underpins this study.

Decisional Control – Approach to Experimental Design

Decisional control in the experiment.

In the present experiment, we recorded psychophysiological changes, time of decision-making, and stress ratings for repeated presentations of decision scenarios in a two-level hierarchy involving three levels of freedom of choice (Choice Structure: *Cc*, *Nc*, and *Nn*), and two levels for number of choices (Element Set Size: two or four).

Contextualizing decisional control as a form of stress negotiation.

Decisional control involves coping with psychological stress through decision-making. Decisional control contrasts with *behavioral control*, directly acting to remove a noxious stimulus, and *cognitive control*, mentally re-calibrating stress reactions (Averill, 1973). *Decisional control* involves action as the result of systematic thinking. Decisional control has been modeled as a pattern of quantities in decision-making structures (Morrison, Neufeld, Lefebvre, 1988; Neufeld, 1982). These quantities have been defined as: 1) *decisional control*, ‘number of available responses’ (actual options), 2) *information processing demand*, the number of possibilities to consider (potential outcomes, regardless of choice input), and 3) *expected threat*, the cumulative likelihood of stressor occurrence in the wake of decisional control implementation across all threat values that

may be obtained in a decision scenario. In more comprehensive discussions of the model, a third condition, Uncertainty, is included as a possible choice condition along with Choice and No-choice. In the present study, no Uncertainty conditions were used. As such, information processing demand is described as ‘number of available responses’, termed Response Set Size or *RSS* to index the cognition requirements of scenarios. Decisional control is indexed, in this study, via probability of access to the least threatening option $Pr(t_1)$, calculated as *RSS* divided by the product of bins and elements (number of bins times number of elements).

For stress and coping resource use, the model allows for balancing the ‘options’, the ‘cost’, and the ‘return on investment’. These correspond to mental processing effort, tolerance of threat in exchange for a certain level of control, and ultimately threat reduction. The potential for threat reduction can be evaluated by assessing prevailing threat in a situation without and with, or again, before and after, the exercise of available decision-making. The model depicts a psychological economy, with plausible mechanisms and openly specified operational terms.

Assumptions of the decisional control model.

Five simplifying assumptions allow for tractability of model properties to statistical calculation. Formal modeling requires stipulation of assumptions within which formal reasoning is made (Neufeld, 2007; Staddon, 1984). Still, model implications are considered to generalize outside of the strict regimen of assumptions (Shanahan & Neufeld, 2010), which to some degree are specified to facilitate computation. The assumptions within the decisional control model in use within this study are:

- 1) *maximax* decision-making (*maximize* the *maximum* advantage)
- 2) same number of elements in each node (bins, elements) at a given hierarchy level
- 3) mutually exclusive threat values (a definite single rank-order)
- 4) equal likelihood of external assignment among co-nested options (random selection)
- 5) necessity of a selection (no ‘escape’)

The strategy of *maximax* decision-making refers to *maximizing the maximum advantage*, shortened to *maximax* (cf., Janis & Mann, 1977). The model convention is that threat values are ordered according to increasing threat values, $t_1, t_2, \dots, t_{\max}$, where t_{\max} is the highest threat value. A *maximax* decision strategy prescribes that if t_1 is available it will be the decision maker’s target; if t_1 is not available, then t_2 , and so forth. As a contrast, a different decision-making strategy could be *minimax* whereby a conservative decision maker seeks to minimize the maximum *disadvantage*. This would entail a decision pattern of avoiding the worst t value.

Advantageous features of the decisional control model.

Findings from experimental designs anchored in a formal model of decisional control (Benn, 1995, 2002; Kukde & Neufeld, 1994; Morrison, Neufeld, & Lefebvre, 1988) support the utility of the model. Decisional control in these studies has been related empirically to psychophysiological reaction among participants. On the theoretical side, comprehensive simulation research has detected robust patterns of a high negative correlation of availability of the best option to the decision-maker and cumulative threat expectation across a scenario. In the picnic example earlier, cumulative threat expectation

is comparable to total accumulation of rain over several instances of using decisional control. Past simulation findings inform the present analyses and invite validation of potential hypotheses (Shanahan & Neufeld, 2010).

The advantages of this modeling approach are: 1) mathematical independence from situational details, such that if a balanced, nested decision structure and rank-ordering of threat values is present, the probability of obtaining lower or higher threat values are retained regardless of threat content or particular authority frame, 2) applicability to hierarchical structure (nested decision-making, arguably ecologically valid where decisions are contingent on other decisions) and 3) the incorporation of number of options (number of bins and number of elements) as formal algebraic variables (denoted as p bins and q elements-per-bin).

Psychometric Instruments Relating to Decisional Control

The scales selected as background psychometric measures for this study relate to decisional control in specific ways. Relevant to the individual differences in the dependent variables, instruments relating to anxiety and uncertainty were selected. These are the Ender Multidimensional Anxiety Scales – Trait (EMAS-T; Ender, Edwards, & Vitelli, 1991; Ender, Edwards, Vitelli, & Parker, 1989), and the Uncertainty Response Scales (URS; Greco & Roger, 2001). Relevant to the impact of independent variables, instruments relating to decisional control were selected to inform appreciation of individual profiles. These are the Desirability of Control scales (DOC; Burger & Cooper, 1979) and the Need for Cognition scales (NFC; Caccioppo & Petty, 1982; Caccioppo, Petty & Kao, 1984). Relevant to measuring control variables not directly part of the experimental manipulation but potentially acting as confounds were demographic

information, manipulations check questions and a brief test of cognitive ability (Wonderlic Personnel Test, Wonderlic & Hovland, 1939; Wonderlic Inc., 2002). Finally, subjective ratings of stress were collected after each trial as a main dependent measure.

Psychophysiological Measurement of Decisional Control

Previous work has indicated that psychophysiological measures can successfully discriminate between prevailing decisional-control conditions (Kukde & Neufeld, 1994). Facial electromyography, skin conductance, and heart rate measures have been significantly related to experimental manipulation of decisional control. Blascovich and colleagues (see, e.g., Blascovich, 2008) have also used heart rate, cardiac output, pre-ejection period, and vascular resistance measures to measure the impact of personality-oriented cognitive manipulations.

Psychophysiological measures are used in this study to assess the impact of constructs from the decisional control paradigm. Variance in psychophysiological measures obtained with cardiac impedance technology is expected to correspond to visually-presented decision scenario features for which instruction and practice in paradigm-consistent responding has been given.

The psychophysiological measures used are briefly described here in their operation and assessment. Heart rate is measured through cardiac impedance technology, whereby an imperceptible electric micro-charge is used to assess the flow of blood through the chest cavity. Measures of particular interest are maximum and minimum heart rate, averaged in this experiment over 6 identical repeated trials per cell condition. Also used in testing the principal hypotheses was total peripheral resistance (TPR), a

measure of vascular resistance considered to vary with the experience of increased stress, especially in stress due to a sense of threat. This and other psychophysiological measures have been successfully used in personality and individual differences research by Tomaka, Blascovich and colleagues (e.g., Blascovich, Seery, Mugridge, Norris, & Weisbuch, 2004; Tomaka, Blascovich, Kibler, & Ernst, 1997).

Statement of Study Hypothesis

Our hypothesis is threefold. First, levels of *Choice Structure* with more decisional control will be significantly negatively associated with stress. This hypothesis is driven by existing findings suggesting that lack of control in decisional control scenarios is particularly stressing (Kukde & Neufeld, 1994; Morrison, Neufeld, Lefebvre, 1988). Second, the number of options in a scenario, or *Element Set Size*, will be significantly associated with increased stress. This hypothesis is driven by the stress related to the prospect and execution of increased information processing, especially under implicit time constraints. Third, if an interaction is found between *Element Set Size* and *Choice Structure*, it is expected that higher *Element Set Size* will enhance *Choice Structure* when it is higher in decisional control (*Cc*, *Nc*, *Nn* in decreasing order) to raise stress due to increased cognitive load required for threat reduction.

Methods

The design of the methods used in this study warrant a detailed introduction. In order to assess stress response within the decisional control paradigm with an informative individual differences background profile, several specific approaches were incorporated into the design. To begin, several modes of data for each participant were cross-

referenced, permitting a close following of personal interaction with decisional control conditions and fine-tuned comparison between participants. The psychophysiological portion of the experiment was fully randomized within participants, such that all participants received all six (3 x 2) experimental cell conditions, each with six identical repeated trials for reliable measurement, a total of 36 experimental trials. A choice-preference portion of the experiment was conducted prior to the data collection for the present study but with the same participants in the course of the same overall experimental session. This first portion of the experiment involved 180 trials with participant selection between different decisional-control structures, paired with either a physical danger prompt or an ego-threat prompt. The pattern of participant selection was then modeled rigorously using an elimination-by-aspects (see Tversky, 1972; also see Batsell, Polking, Cramer & Miller, 2003) decision framework and set of equations for the generation of choice preference parameters through optimization procedures within the standard MATLAB (version 7.5, 2007b) software package (Pawluk, Shanahan, Hong, Neufeld, 2008).

In the main portion of the experiment for the study reported here, the portion of the experiment enacting decisional control used a detailed design to collect a 'duration of decision-making' time period measure. Distinct from the immediately subsequent time period used for effectuation of the motor movement for response registration (pressing a letter response on a key board), the time of decision-making cognition reflects the time spent mentally evaluating and selecting a desired option. As such, the present study validates and refines understanding for the operation of decisional control within a psychophysiological, personality and individual differences, and cognitive psychology

framework. It also is an extensively cross-indexed data set with potential for new analyses for questions in cognition, personality, and decision-making.

Participants

Participants were recruited via posters or from an introductory psychology pool at a large central Canadian university. The initial sample consisted of 36 male and 35 female students (N = 71; Age *M*= 22.7, *S.D.* = 5.5, *Min.* = 18, *Max.* = 44, *Mode* = 20, *Median* = 21).

Procedure

Initial & learning phases.

Informed consent was obtained, after exposing the prospective participant to two seconds of white noise in a headset with controlled decibel level to inform the participant of relevant study features. Written instructions first coached participants about a set of probabilities that unpleasant white noise would be administered, assigned to each of 10 different letters, as below:

Table 2

Letters for Stimulus Presentation and Associated Probabilities

D	B	J	L	M	A	Z	V	P	G
.30	.35	.40	.45	.50	.55	.60	.65	.70	.75

The participants were then instructed to order the letters into the order shown in Table 2 above out of a scrambled order, rank ordering correctly from lowest (e.g., Rank 1, ‘D’, 30% chance) to highest (Rank 10, ‘G’, 75% chance). If done incorrectly,

feedback was provided and the participant tried again. The next stage did not begin until this ordering was done correctly.

Participants were acquainted with schematic depictions of decisional control scenarios in three steps. First, as the basis of a recurring stress prompt, they read situational vignettes (as in Figure 2.1, below). Second, these vignettes were summarized into simple titles for in-trial reference (e.g., “Job Interview”). Third, participants were taught and practiced how to access available decisional control as depicted in hierarchical, coloured-box patterns (Figure 2.2).

Figure 2.1. Excerpt from Vignette Presentation Portion of Experiment

Boating / Lightning Storm [example for evocation of Physical Danger]

You are boating with a friend on a large lake when a thunder/lightning storm approaches. There are two islands which are still visible on the lake. You recall that there are eight different possible landing sites from which you may choose. [structure: Cc]

Oral Presentation [example for Ego Danger / Social Evaluation]

Your new position requires you to deliver oral presentations for critical analysis by one superior assigned from two possible. You may choose the subject of these presentations from amongst eight given subjects. [structure: Nc]

Formal Debate [Ego Danger / Social Evaluation]

In order to fulfill your degree requirements, you must successfully complete the Communication 020 course which requires each student to formally debate an issue with one other fellow student, to be followed by questions and class discussion. One of two opponents will be assigned to you, as will your specific issue for debate amongst the eight available. [structure: Nn]

Figure 2.1. Examples of stressful vignettes training presentation; in square brackets are commentaries added for the figure, not presented to participants. Note, eight options are mentioned in each case, with all, half, and only one made available by further description.

Figure 2.2. Example of Graphical Depiction of an Nc2 Decisional Control Scenario

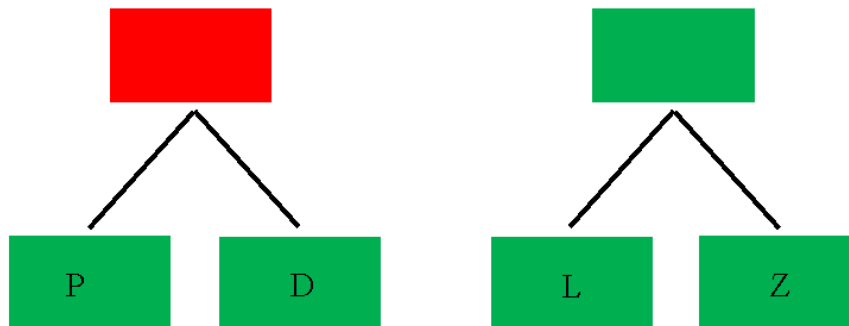


Figure 2.2. An Nc2 (No-choice, Choice; $q = 2$) decisional-control hierarchy presentation

The situational vignettes used to depict stressful scenarios focused on two kinds of threat, one to physical well-being (threat of serious injury), the other to personal ego, or sense of self as a social being (threat of embarrassment, humiliation, loss of status. These types of awareness of threat are recognized as some of the main sources of stress action (Eysenck, 1989; Mothersill, Dobson, & Neufeld, 1986). Use of vignettes in simulating threat or stress is an established personality and individual differences method that is supported for eliciting stress in participants that is experienced similarly to the stress in the situation described, though to a lesser magnitude (Lanza & Carifio, 1990; van den Tooren & de Jonge, 2010). Once participants had been familiarized to the story of each vignette, only the referent titles were used to help participants recall the stressful situation in navigating a presented decisional control scenario. The full text of the six

vignettes used in this experiment is available from the first author. Titles of each vignette, describing briefly the situation and practical threat, were the vignette situations were “Skiing / Blizzard”, “Driving / Icy Roads”, and “Boating / Lightning Storm” for physical threat. For social evaluation or ‘ego threat’ the vignette titles were: “Oral Presentation”, “Formal Debate”, and “Job Interview”. These titles were randomly associated in advance with the various decisional control hierarchies to be navigated.

The hierarchical arrangement of decisional control for each scenario was depicted with rectangular boxes of identical size with full element sets visible as nested within bins, connected by simple straight black lines. The “Choice” condition was depicted by a green box on all equivalent options at a given hierarchy level (i.e., under Cc all bins and elements were green; under Nc , the assigned bin and all elements were green; excluded bin was red, such that its nested array of green elements were not accessible through the hierarchy, see Figure 2.2). The “No Choice” condition at a given node (either a bin- or element-level box) was depicted by a red-colored box for all equivalent options except for a green-colored box on the only available option. The rationale for the coding was that a ‘green’ option was available for selection, whereas a ‘red’ option, and any options under it, had been eliminated by decision-making external to the participant.

Participants were given three practice trials to learn accurate decisional-control responding. They were presented with singular graphic stimuli. Tags on the stimuli had letters randomly selected from the previously presented 10-letter set. Participants were informed that white noise would be presented at the end of the first phase of the experiment and the duration of the noise would be contingent on their performance on the accuracy practice trials. In actuality, the duration of noise administered was to be

randomly determined, between 1 to 4 seconds. During the experimental trials, no feedback regarding judgment accuracy was provided and no white noise was administered.

In the psychophysiological testing area, participants sat facing a computer screen, with button box to record preferences for a presented scenario. Eight buttons were available to allow the participants to indicate their choice directly if there were eight options presented. When *Element Set Size* $q = 2$, only four options were presented. In these cases the two sets of outer-edge buttons on the full set of eight were indicated as corresponding to the four boxes on the screen (as buttons 1, 4, 5, and 8, seen in Figure 2.3, Apparatus section, below).

Threat values across presentations were controlled by sampling randomly from the list of 10 threat levels depicted by proxy through a letter stimulus (D, B, J, ..., G). Specifically, when four elements were used, they were randomly chosen without replacement from the list of 10, and when eight elements were used, they were also selected without replacement from the list of 10. The experimental design thus provides an approximately balanced set of threat option values.

A 'teacher's desk bell' was placed on the computer desk within the participant's reach to notify the experimenter of completion or to request assistance. Following the general procedure outlined in Kukde and Neufeld (1994), the protocol for the experiment proper is listed below.

Psychophysiological measurement and decision-making response phase.

Prior to any presentation of stimuli, baseline psychophysiological measures were collected after the participants were fitted with the psychophysiological apparatus. Six practice trials were given to familiarize the participants with the experiment layout. A different set of 10 letters and their associated probabilities were presented for their reference. Participants also practiced registering subjective stress ratings at the end of each practice trial. Participants were given time to re-learn original threat levels associated to letter stimuli.

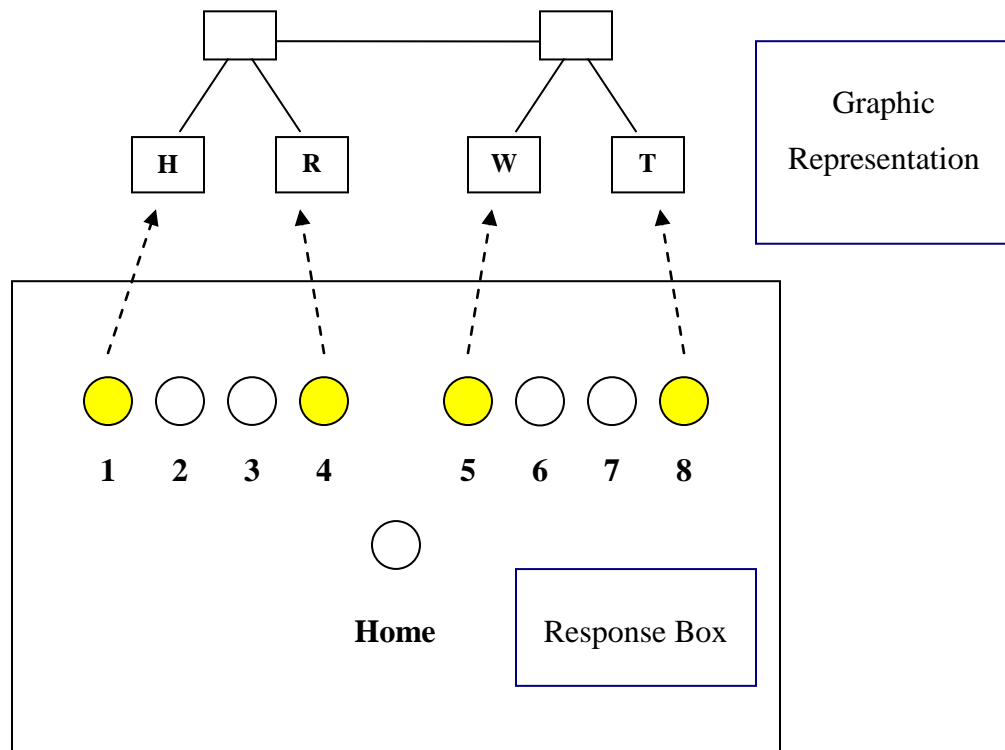
The goal of the practice phase was to minimize stress reaction during actual testing and prevent confounding with stress associated with uncertainty and anxiety due to the inability to remember. After the re-learning phase, participants' cognitive appraisal of potential challenge or threat was verbally assessed (see Blascovich et al., 2004; Lees & Neufeld, 1999). Care was taken to ensure that participants understood the appraisal was to be done with reference to upcoming actual trials and not the previous practice trials.

In total, there were 36 experimental trials per participant. These followed a 3 x 2 within-subjects design, with these factors: 3 levels of *Choice Structure* (i.e., *Cc*, *Nc*, and *Nn*), and 2 levels of *Element Set Size* (i.e., $q = 2$ or $q = 4$, q represents elements-per-bin). Each unique combination was presented as an experimental trial six times. Participants were given one of the three pre-arranged random orders of stimulus presentation. These orderings were a control condition to minimize the prospect of order effects. After this phase psychophysiological apparatus was removed and participants completed the psychometric and manipulation check instruments listed in Materials, further below.

Apparatus

The apparatus used in the first phase of the experiment was a computer with a Windows 3.1 operating platform. Programming of the instructions, practice and actual trials was done in Visual Basic. Headphones and a box for administering white noise were shown to participants. The design of the response button box is shown in Figure 2.3 below.

Figure 2.3 Representation of Button Box Configuration for Registering Responses



Apparatus for the psychophysiological research was based on apparatus used for personality-related cognitive variables (Blascovich, et al., 2004; Tomaka, Blascovich, et al., 1997). A Biopac Systems MP-150 data collection apparatus was used to coordinate electronic signals for cardiac impedance-based measurement. This unit was augmented with STP-100 module, and also included the UIM 100C, EBI100C, ECG100C, and DA100C Biopac modules.

Ten electrical leads were placed bilaterally (left and right) on participants (note, more leads can be added to obtain other data such as skin conductance, electro-myographic and respiration rate). Two leads were affixed at the top of the neck below the back of the jaw, two at the base of the neck in line below the upper two electrodes, two on the breastbone and two pairs at the upper and lower end of the rib cage. One more monitor was placed in the middle of the chest for heart rate calculations. Past research has shown that heart rate measures, including the calculation of a minimum heart rate in a given trial (heart rate deceleration, or HRDEC) can be sensitive to changes in decisional control variables such as choice structure (e.g., Morrison, Neufeld, & Lefebvre, 1988). Data was collected on a computer in an adjoining room, using the AcqKnowledge software package, version 3.7.2, associated with the Biopac data collection apparatus.

Materials

Wonderlic Personnel Test.

The Wonderlic Personnel Test (WPT; Wonderlic & Hovland, 1939) is a 12 minute paper-and-pencil test of cognitive ability. Due to the importance of cognitive processing in this research, cognitive ability is assessed. Past research (e.g., Benn, 1995,

2002) suggests that cognitive ability does *not* correlate with affinity for information processing in a decisional control paradigm. The WPT is a standard industrial psychology assessment tool and provides a good prediction of general intelligence, as supported by comparison with other standard measures such as the Wechsler Adult Intelligence Scales (e.g., .93 correlation with WAIS FSIQ in Dodrill, 1981; differences less than 1.3 with WAIS FSIQ scores in Dodrill and Warner, 1988; .92 correlation with WAIS-R in Hawkins, Faraone, Pepple, Seidman, Tsuang, 1990; foregoing studies, all as cited in Restrepo, 2008).

Endler Multidimensional Anxiety Scales – Trait.

The Endler Multidimensional Anxiety Trait Scales (EMAS-T; Endler, Edwards, & Vitelli, 1991) have four subscales: Social Evaluation, Physical Danger, Unfamiliar situations, and Routine. There are 15 statement items endorsed from 1 (Not at all) to 5 (Very much). The 15 statements are identical between the four subscales and include items such as: “Seek experiences like this”, “Have an ‘uneasy feeling’”, “Feel secure”, and “Feel anxious”. The difference between the four subscales is the preface to each 15 item set. One asks participants to answer as if “You are in situation where you are being evaluated by other people” (Social Evaluation). Physical danger, new/unfamiliar situations, and daily routines are similarly primed as the context within which to rate the same 15 items. Reliability coefficient alpha is reported as .85 or higher on all sub-scales for both males and females (Endler, Parker, Bagby, & Cox, 1991). In the present sample, we calculated the reliabilities for the four scales: Social Evaluation ($\alpha = .87$, 15 items, 70 cases), Physical Danger ($\alpha = .88$, 15 items, 69 cases), New/Unfamiliar Situations ($\alpha = .85$, 15 items, 69 cases), and Routine ($\alpha = .87$, 15 items, 69 cases). These values are

consistent with the aforementioned previously published results (Endler, Parker, Bagby, & Cox, 1991).

Physical danger and social evaluation are of particular relevance in our experiment as these types of situations are reflected in the design of the stress-prompting vignettes (e.g.: physical threat, “Driving / Icy Roads”, “Boating / Lightning Storm”; social evaluation, “Oral Presentation”, “Job Interview”). In addition, the New/Unfamiliar Situations and Daily Routines sub-scales provide valuable background and often converse results in the tendency to feel anxious in new situations or by contrast, in daily routines.

Need for Cognition scale.

The Need for Cognition Scale (NFC; Cacioppo & Petty, 1982; Cacioppo, Petty, & Kao, 1984) is a measure designed to assess an individual personal disposition to desire information processing and thinking as part of any given activity. This scale has been used effectively in previous decisional control research, supporting a personality-dependent view of decisional control preference (Benn, 1995, 2002) over an ability-dependent view. The NFC is an 18-item scale rated on a nine-point interval between -4 (very strong disagreement) and +4 (very strong agreement). Sample items include: “I would prefer complex to simple problems.”, “I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought.”, and “I would rather do something that requires little thought than something that is sure to challenge my thinking abilities” (reverse scored). Strong internal consistency, with Cronbach’s alpha of .90, is reported (Cacioppo, Petty, & Kao, 1984),

supporting a single dimension for the NFC scale. Using all data available (without exclusions) we calculated an internal consistency of .90 for Cronbach's alpha in our sample (18 items, 70 cases).

Desirability of Control scale.

The Desirability of Control scale (DOC; Burger & Cooper, 1979) is designed to assess "general level of motivation to control the events in one's life". It is a 20-item measure, with a 7-point scale ranging from 1 (This statement doesn't apply to me at all.) to 7 (This statement always applies to me.) Sample items include: "I prefer a job where I have a lot of control over what I do and when I do it", "When it comes to orders, I would rather give them than receive them", and "Others usually know what is best for me" (reverse scored). A Kuder-Richardson 20 reliability statistic is reported as .80 and a test-retest reliability of .75 (Burger & Cooper, 1979). In our sample internal reliability is consistent with published research, with a Cronbach's alpha of .81 (20 items, 71 cases).

Uncertainty Response Scales.

The Uncertainty Response Scales (URS; Greco & Roger, 2001) are designed to assess modes of coping with uncertainty. Factor analysis work has confirmed three subscales for individuals' patterns of coping with anxiety: emotional uncertainty, desire for change, and cognitive uncertainty. Sample items for emotional uncertainty, wherein the reaction to uncertainty is primarily emotional, include: "I feel anxious when things are changing", and "Uncertainty frightens me." Sample items for desire for change, a subscale related to an eager and anticipatory attitude towards uncertainty, include: "I find the prospect of change exciting and stimulating", and "I think variety is the spice of life."

Sample items for cognitive uncertainty, characterized by an awareness of a lack of factual knowledge and understanding of an uncertain situation, include: “I like to plan ahead in detail rather than leaving things to chance”, and “I like to know exactly what I am going to do next.” Items are rated on a 4 point scale, presented as “Never, Sometimes, Often, Always” (scored as 0 to 3). Coefficient alpha for the three subscales is reported as: .89 (emotional uncertainty), .90 (desire for change), and .85 (cognitive uncertainty). The test-retest reliability statistic is reported as .79, .86, and .80, respectively. In the present sample, the coefficient alpha for reliability was calculated as .86 for Emotional Uncertainty, .89 for Cognitive Uncertainty, and .90 for Low Desire for Change.

Manipulation-check questions.

Psychometric scales for related constructs (as described immediately above), control variables and demographics, and subjective self-report data were collected after the experiment so as not to inordinately sensitize participants to experimental variables. A series of manipulation check questions were presented to ascertain the strength of the experimental design. This type of verification has precedent in research involving perception of control (Dobson & Neufeld, 1989). Four questions were asked (presented below), with endorsement between 1 and 9 on a Likert-type scale. Written anchoring descriptors for questions 1 and 2 were: 1 - “No control at all”, 5 - “Moderate control”, and 9 “Total control”. Written anchoring descriptors for questions 3 and 4 were: 1 “Not at all willing”, 5 “Moderately willing”, and 9 “Extremely willing”.

1 – During the letter-selection task, how much control do you feel you had in reducing the amount of white noise to be administered to you?

2 – During the letter-selection task, how much control do you think other participants (doing the same task as you did) had in reducing amount of white noise administered to them?

3 – When dealing with stressing situations, to what extent would you be willing to process information that enables you to reduce threat?

4 – When dealing with stressing situations, how willing are you to tolerate threat, rather than to process information that can reduce it?

Results

Data

Data types.

Three types of data are used in this research design. The use of formal modeling permits the generation of ‘method data’, an *a priori* furnishing of expectancies with its own set of statistical properties, and specific point estimates. In this way, model-driven ‘method data’, derived from instantiation of modelled quantities for specific experimental levels creates a type of data that might be termed the ‘modus’ (Latin for ‘method’).

The data as commonly understood, (*data* the plural of *datum*, Latin for ‘what is given’) summarizes the dependent variable measurements. Finally, a third ‘terrain’ exists which is properly distinguished both from ‘method’ (modus) and ‘givens’ (data): the context within which these both occur and do or do not match up to one another. The expected influence of psychometric backdrop, the individual differences landscape, can

be named the ‘topothesis’, “the logic of the place where the idea is laid down”. The matrix of related construct variables can be considered the ‘topic data’, and might be called by a fitting neologism the ‘topia’.

Linguistic inventions aside, the three types of data can be conventionally referred to as: ‘method-driven’ (model predictions), ‘empirically-acquired’ (data collected under experimental manipulation) and ‘background inventories’ (psychometric-type data).

Besides this trifecta of data types, the data collected by experimental means in this multi-modal study can be classified in two large categories: individual difference variables, and experimental trial variables. The individual difference variables include administrative counts (participant number, trial order), demographic variables, manipulation-check ratings, published psychometric instruments, and modeled decision-choice preference parameters. The experimental trial variables include psychophysiological measures, reaction time data, and per-trial subjective stress ratings.

Individual difference variables.

Administrative, demographic, and psychometric instrument data.

Among the individual difference variables, administrative counts were Participant Number (sequential within data collection dates) and Trial Order (three randomized orders were alternated). Demographic variables are Sex and Age. Manipulation check ratings were collected using four questions to assess for effectiveness of the experimental manipulation. Published psychometric instruments used were: the Wonderlic Personnel Test, the Desirability of Control scale, the Need for Cognition scale, the Endler

Multidimensional Anxiety Scales – Trait (subscales: Social Evaluation, Physical Danger, Unfamiliar Situations, and Routine), and the Uncertainty Response Scales (subscales: Emotional Uncertainty, Low Desire for Change, and Cognitive Uncertainty).

Individual choice preference profiles.

Elimination-by-aspects preference parameters.

The final set of individual difference variables are the modeled decision-choice preference parameters. Data was collected in an initial stage of the full experimental session for participant preference between Cc , Nc , and Nn scenarios, always with two bins randomly mixed for two and four elements per bin. Over 180 selections were made by participants, and these were modeled into preference parameters, reflecting relative preference for choice. These involve a total of eight parameters, four relating to ego-threatening situations, and four relating to physically dangerous situations. In parallel, each of these two types of situations has four parameter values optimized for fit to an elimination-by-aspects decision-making model (Tversky, 1972; see also, Batsell, Polking, Miller & Cramer, 2003), allocating individual relative preference for features of decision-making scenarios presented in the first phase of the experiment. This modeling method has been used successfully in previous research (e.g., Morrison, Neufeld, & Lefebvre, 1988). The four parameters are: 1) parameter a , related to decision features unique to full choice scenarios (Cc only), 2) parameter b , decision features shared by mixed choice scenarios and pure no-choice scenarios (Nc and Nn), 3) parameter c , decision features unique to pure no-choice scenarios (Nn only), and 4) parameter d , decision features

shared by full choice and mixed choice scenarios (C_c and N_c). The result is a subset of four parameters each for ego-threatening and physically dangerous situations.

Optimization and calculation of preference profiles.

Optimization was done with a range for possible values from .001 to 999.000, to allow for a suitable degree of variation in order of magnitude between parameters. Higher values indicate increased preference for a given particular feature of a choice scenario. These preferences were summarized on a single dimension (see “Maximizing Continuum”, next paragraph). This optimization and main findings from the first phase of this experiment are reported elsewhere (Pawluk, Shanahan, Hong, & Neufeld, 2008). However, one change in the present analysis is that the four variables were permitted to vary freely, rather than setting parameter c equal to 1 as was the approach in previous analyses. A second change involved creating within-subject proportions for the four variables, such that the sum of the four ego and four danger parameters were used as the denominator in allocating a proportional preference between the four parameters (Shanahan, Pawluk, Hong, & Neufeld, 2012). This allows comparison between participants, and improved psychometric properties.

A new measure of decision preference: the Maximizing Continuum.

The development of a “Maximizing Continuum” took its impetus from the availability of these standardized parameters. On the same sample as in the present report, a successful development and validation of a “Maximizing Continuum” as a decision-making tendency was developed (Shanahan, Hong, Pawluk, & Neufeld, 2012). This involved the sum of the choice-oriented parameters (parameters a and d), and the

subtractions of the choice-averse parameters (b and c). The scale that emerges has robust properties and specified ranges for three decision-making preferences: Maximizing (a desire for maximal result, accepting the attending information processing demands), Satisficing (a desire for a ‘good enough’ result, seeking an intermediate amount of information processing), and Simplifying (a preference for limited information processing, with acceptance of minimal decision-making advantage). Using these definitions, previous datasets were reviewed and the prevalence of the three decision-making preferences, Maximizing, Satisficing, and Simplifying was found to occur with these as reliable factors in previous analyses (Benn, 1995, 2002).

The Maximizing Continuum is used in the present study in constructing a psychometric profile for individual participants. As reported in the Main Analysis, under Results, a factor score relating dominantly to Maximizing exhibits a significant covariate interaction with Choice Structure within the experiment. Although covariate interactions can be considered nuisance effects, in this context it is a construct validation of expected overlap between the constructs of preference for control (Maximizing) and availability of decisional control (Choice Structure).

Experimental trial variables.

Psychophysiological measures.

Experimental trial variables were maximum and minimum heart rate, total peripheral resistance, decision-making time, and subjective stress rating. Maximum heart rate indicates degree of arousal and has been used to detect a ‘challenge’ response to stressful situation (e.g., Blascovich et al., 2004). The short form for maximum heart rate is

HRACC, as it is an indicator of acceleration in heart rate. For minimum heart rate, the lowest heart rate recorded during a particular trial is an indicator of deceleration in heart rate for that trial. The short form for minimum heart rate is HRDEC. Based on previous research (see Kukde & Neufeld, 1994; Morrison, Neufeld, & Lefebvre, 1988), a lowered minimum heart rate can be an indication of increased information intake (c.f. Lacey & Lacey, 1974). This may also be compared with increased 'focus', or a quieting of physiological function to prioritize higher-order cognition. Morrison and colleagues (1988) found that minimum heart rate was at a maximum in scenarios with the least decisional control (e.g., *Nn* condition) and at a minimum in scenarios with most decisional control (*Cc*, *Nc*). This may result from a combination of increased information intake combined with lack of decision-making power. A qualitative impression for this pattern of participant mental and physical status is that of a physiological 'self-calming' and cognitive 'focus' when mentally effortful threat reduction is available, and an increased physiological arousal and undifferentiated cognitive 'alertness', when threat can be met but not managed.

Total peripheral resistance TPR is an index of 'resistance to blood flow'. It is calculated as the drop in mean arterial pressure registered after one systole, or a cycle of blood fully through the circulatory system, as divided by cardiac output, or the volume of blood flow per unit time. More involved discussions of TPR are available elsewhere (e.g. Blascovich et al., 2004); for the purposes of this study this measure serves as a screen at the psychophysiological level for reduced blood flow often associated with the experience of being threatened under stress.

The values used for psychophysiological measures are reactivity scores. These are differences between the experimental cell condition means for the participant's psychophysiological readings during the experimental stimulus presentation (trial) and the experimental cell condition means for the same participant during a thirty second resting period immediately prior to each stimulus presentation (baseline). For example, a positive value for minimum heart rate reactivity score indicates that during the trial, participants did not return to resting levels for minimum heart rate.

Psychophysiological scores were averaged across the six identical repeated trials to provide an estimate of a peak and lowest heart rate for participants that characterized their encountering a specific decision scenario (*Cc2, Cc4, Nc2, Nc4, Nn2, Nn4*).

Decision-making time and stress ratings.

The other two experimental trial variables are decision-making time and stress rating. Decision-making time RT1 is defined as the time taken by the participant to assess the scenario and make a decision regarding an optimal selection for lowest threat within decisional control constraints. This involved the pressing and holding of the 'space bar' key on a standard personal computer keyboard. The pressing of the space-bar initiated the presentation of the decision scenario, with little or no delay between the press and the presentation (< 50 ms). Subsequently, once a decision was made, the participant was to register their letter selection by pressing the appropriate letter key with the same hand as had been holding down the space-bar. The act of releasing the space-bar acts as an end-marker for the time period of decision-making (decision-making time, RT1, from "reaction time 1"). This approach was closely coached for participants and was

periodically verified by the experimenter as actively being used throughout each experiment for continuing construct validity for the 'decision-making time' measure. Within the set of valid participant cases, the range of reaction times was a minimum of 931 milliseconds and a maximum of 7069.7 milliseconds.

Stress ratings involved the presentation after each trial of a Likert-type scale with five anchor points in answer to the question: "How stressed were you during that trial?" The verbal descriptors matched anchor points as follows: 1 – No Stress, 2 – A Little Stress, 3 – Moderate Stress, 4 – Considerable Stress, 5 – Extreme Stress. This question was presented after each of the 36 experimental trials and a value from 1 to 5 was collected as a *single-trial rating of subjective stress* (STRSS). Use of subjective ratings of stress is common with research involving physiological or psychophysiological efforts and demands (e.g., Siegwarth, Larkin, & Kemmner, 2012; Stamford, 1976).

Data processing.

Age exclusion.

From the original sample of 71 participants (35 female, 36 male), six were over age 30 (range 32-44, 3 female, 3 male). Removal of these participants is supported by a tendency for a change in physiology that can affect cardiac impedance recordings (cf., Denburg et al., 2007). This sub-group also contributed additional confounding with a disproportionate number of outliers for psychophysiological and psychometric covariate measures. Participants aged 30 years or more were removed from the sample. For future consideration, participant Age should be kept within ranges most likely to vary with some

uniformity. In our study, this was the 18-29 years range. After Age exclusion, our sample consisted of 65 participants (32 female, 33 male).

Psychometric instruments and choice preference parameters.

No participants were excluded based on their scores on published psychometric instruments. The properties of these scales are robust and remained within acceptable ranges for analysis. Among the choice preference parameter values, their standardization via the use of proportions allowed these values to become comparable between participants and useful for analyses. An important caveat for the Maximizing Continuum is the disproportionate distribution toward Maximizing. In the Ego-Threat parameter set, there were 49 Maximizers, 20 Satisficers, and 2 Simplifiers; in the Physical Danger parameter set, 53, 16, and 2, respectively. However, the Maximizing Continuum is a continuous measure as its name suggest, such that interval differences are considered meaningful. As such, the participant scores on a Maximizing score for both sources of threat combined yielded a measure of Maximizing suitable for use in the factor analysis that was undertaken to create an individual psychometric profile of participants.

The covariates generally, both psychometric instruments and modeled preference parameters, are intended to reflect individual difference meaningfully, and so it was fitting that once these became comparable and, or, distributed suitably, all individual difference variables data were kept within the main analysis. This was done even with the concern for entire sets of missing psychophysiological data on a participant-wise basis. However, in order to preserve the characteristics of the sample population, participants excluded via the Age criterion were not re-introduced into the sample. In sum, the sample

of 65 participants was drawn from a comparable population of 18-29 year-old undergraduates, generally.

The psychophysiological data were complete or nearly-complete for 49 participants, but 16 participants' psychophysiological datasets were largely missing due to apparatus and methodological challenges. These kind of experimental issues are not uncommon with psychophysiological research even with state-of-the-art implementation, as was used in our study with up-to-date methodology (e.g., as per Blascovich et al., 2004). Notwithstanding missing data, the analysis done on the full set of 65 participants returned the same results as a control analysis with only 49 participants in terms of psychophysiological sensitivity to independent variables, such that the software analysis platform (SPSS 22.0) compensated suitably for missing data.

Psychophysiological measures.

Using an established research paradigm (Blascovich, Seery, Mugridge, Norris, & Weisbuch, 2004; Kelsey, Blascovich, Leitten, Schneider, Tomaka, & Wiens, 2000; Tomaka, Blascovich, Kelsey, & Leitten, 1993; Tomaka, Blascovich, Kibler & Ernst, 1997), we successfully collected data from the majority of participants. Some participants' readings were considered invalid due to several factors. Blood pressure readings were affected if the continuously inflating and deflating blood pressure cuff was placed sub-optimally or changed location during testing. Heart rate readings were affected at times by sweating, body fat percentage, and relatively higher levels of localized fatty tissue, such as with females in the breast area. Despite pilot testing and the use of a standardized anatomical schematic drawing, optimal placement of electrodes

seemed to be a skill that could be continually refined with practice for experimenters in order to elicit higher quality data. As such, the resulting data collection tended to yield either an entirely useable set of psychophysiological readings, or a largely unusable set. Erratic readings occurred, potentially due to an electrode slipping due to perspiration or the blood pressure cuff moving during data collection. Notably however, rate of attrition for data quality decreased as the sample increased.

Participants excluded on the basis of missing psychophysiological data nonetheless furnished valid and cohesive psychometric covariate data, both from published instruments and choice preference profiles, as well as decision-making time and stress ratings data. As such the general analyses involving these measures included the full sample of 65 participants, 33 male, 32 female, all under age 30. Factor structure for covariates was replicated with both a full sample of 65 and a full data sample of 49, and main effects and interaction were significant in the same pattern. However, unlike the principal analysis for this study that included psychophysiological variables, no significant interactions were found between the covariates and the decisional control experimental variable levels when no psychophysiological data was used.

Reaction time and trial stress ratings.

Reaction times above 10,000 ms and below 100 ms were eliminated as indicative of construct-invalid responding. A reaction time less than 100 ms was assumed to indicate a lack of deliberation according to instructions, and this time period is a standard cut-off in cognitive science literature (cf., Townsend & Ashby, 1983). The 100 millisecond criterion removed 2 data points as outliers, within a full set of 65 x 3 x 2 x 6

(2340 data points). This is considered a liberal but effective exclusion criterion. The minimum averaged cell-condition reaction time for any single participant remaining in the data analysis was 163 milliseconds.

A response delay over 10 seconds was deemed to indicate distraction not related to the experimental task. By experimental observation and statistical review, this criterion was judged to eliminate definitely confounded responses but allow for the inclusion of responses by participants who spent considerable time evaluating a novel and complex stimulus set. By this exclusion criterion, 28 data points were excluded. In total, with the 100 millisecond floor and 10 second ceiling, 98.7 % of the data remained valid. Importantly, no more than three data points were removed from within a given set of six trials in a specific cell condition: average values were always calculated across half or more of all intended trials.

Parametric assumptions.

Control variables and psychometric variables related to this paradigm were examined for parametric assumptions. Participant data (three male and three female) for those aged 30 or over were eliminated from the sample, for consistency among psychophysiological and psychometric variable properties. The resulting sample size of 65 participants thus comprised 33 males and 32 females (Age $M = 21.3$, $SD = 2.7$). Among Control Variables, no major violation of parametric assumptions was observed (Manipulation Check questions 1-4).

Dependent variables were also assessed for parametric assumptions. Across all six conditions, minimum heart rate reactivity values had a mean of 6.055 (beats per minute

increase during task completion), standard deviation of 6.981, a skewness statistic of 3.09 and a kurtosis statistic of 15.55. These values merit consideration for validity; they are outside the typical ranges prescribed for meeting univariate parametric assumptions. However, using a GLM repeated measures model these values can be taken as indicative of trends in participant responding, and not in serious violation the assumption of multivariate normality (Tabachnick & Fidell, 2001). Reaction times across the six experimental cell conditions had a mean of 2304 milliseconds, a standard deviation of 1238 milliseconds, a skewness statistic of 0.82 and a kurtosis statistic of 0.49. Stress ratings across the six experimental cell conditions had a mean of 1.512 (on a 1 to 5 Likert-type scale, from low to high subjective experience of stress during the preceding trial), a standard deviation of 0.557, a skewness statistic of 1.14 and a kurtosis statistic of 0.59. Due to the robust nature of GLM analyses and near-normal distributions of decision-making time and stress rating, the intended 3 x 2 MANOVA analysis was carried out.

Data descriptives.

The correlations reported in Table 3 below are largely consistent with expected relations between variables. NFC and DOC exhibit high moderate positive correlation, and high moderate negative correlation with several anxiety and uncertainty measures. Note the WPT (cognitive ability) is largely uncorrelated with these variables.

Table 3

Correlations among Psychometric Measures

	NFC	DOC	WPT	EMAS – Soc	EMAS – Phy	EMAS – New	EMAS – Rout	URS – Emo	URS – LD
DOC	.49								
WPT	.14	-.08							
EMAS-Soc Eval	-.35	-.40	-.01						
EMAS-Phy Dan	-.22	-.34	.03	.33					
EMAS-New Sit	-.49	-.53	-.13	.56	.39				
EMAS-Rout	-.13	-.21	.08	.12	.09	.37			
URS-Emo Unc	-.50	-.49	-.07	.48	.28	.59	.39		
URS-LD Change	-.48	-.40	-.00	.27	.28	.32	-.02	.33	
URS-Cog Unc	-.02	.20	-.25	.01	-.12	-.11	-.22	.09	.16

Italics typeface: $p < .05$; **Boldface type:** $p < .01$

Note: Table 3 above is intended for description, not to test for significant correlations. Key: NFC, Need for Cognition; DOC, Desirability of Control; WPT, Wonderlic Personnel Test; EMAS, Ender Multidimensional Anxiety Scales: Soc, Social Evaluation, Phy, Physical Danger, New, New/Unfamiliar Situations, Rout, Routine; URS, Uncertainty Response Scales: Emo Unc, Emotional Uncertainty, LD Change, Low Desire for Change, Cog Unc, Cognitive Uncertainty.

Preliminary Analyses

Factor analysis of psychometric instruments.

Given substantial but not excessive overlap between the construct-related variables, a factor analysis was undertaken to distill the data into useable profiles (cf. Tabachnick & Fidell, 2001). With extraction of 51% of the variance, the first three factors in a four-factor solution distill the patterns within the psychometric data and preserve the concurrent benefit of economizing degrees of freedom in the Main Analysis. A principal components analysis was undertaken, using Quartimax rotation. The Quartimax rotation algorithm allots variance so as to minimize the number of factors. Observing a Scree plot, a plausible ‘elbow’ is found between the third and fourth factors;

the eigenvalue at the third factor was 1.56, at the fourth factor, 1.023, at the fifth factor, .948. The steep drop between factors 3 and 4 recommended the relevance of a solution stopping at the third factor for use of factors as covariates. The fourth factor is included in Table 4, but was not included as a covariate in the main analysis.

Table 4

Factor Loadings for Factor Analysis of Psychometric Scales with Quartimax Rotation

Scale, Sub-Scale or other Variable	Anxious Abdicating	Restless Fidgeting	Steady Maximizing	Obedient Understanding
EMAS – Unfamiliar Situations	<u>.73</u>	<u>.33</u>	.03	-.16
Desirability of Control	<u>-.71</u>	-.15	<u>-.27</u>	<u>-.32</u>
Need for Cognition	<u>-.70</u>	.15	.07	.01
Emotional Response to Uncertainty	<u>.70</u>	<u>.34</u>	<u>-.39</u>	-.00
EMAS – Social Evaluation	<u>.63</u>	.03	.06	-.12
Low Desire for Change	<u>.62</u>	<u>-.39</u>	.07	<u>.25</u>
EMAS – Physical Danger	<u>.44</u>	.02	<u>.42</u>	<u>-.28</u>
Cognitive Response to Uncertainty	-.01	<u>-.54</u>	<u>-.62</u>	-.08
EMAS – Routine	<u>.20</u>	<u>.82</u>	-.07	-.03
Maximizing	.08	-.14	<u>.79</u>	.18
Psychophysiological Data - Full Set	-.00	<u>-.34</u>	-.01	<u>.77</u>
Wonderlic Personnel Test	-.08	<u>.29</u>	<u>.21</u>	<u>.67</u>

Extraction Method: Principal Component Analysis.

Rotation Method: Quartimax with Kaiser Normalization. Rotation converged in 5 iterations.

EMAS: Ender Multidimensional Anxiety Scales

*Factor loadings > .40 are in **boldface underline**, .20 < factor loadings < .40 in underline only.*

First factor: Anxious Abdicating.

In the factor analysis, the first factor accounted for 25.4% of the variance within the rotated solution, with an initial eigenvalue of 3.171 on the unrotated version of this factor. The first factor seems to capture the tendency of high anxiety and tendency to an emotional response to uncertainty, together with a marked lack of desire for control and similarly marked lack of need for cognition. As such, this factor received the descriptive name “Anxious Abdicating”.

Second factor: Restless Fidgeting.

The second factor accounted for 13.4% of the variance within the rotated solution, with an initial, unrotated eigenvalue of 1.73. The second factor seems to capture the tendency for the experience of anxiety stemming from routine, a negative tendency to low desire for change, or, some degree of *positive* desire for change. Additionally, there is an illuminating if secondary preponderance within this factor: there is some correlation with poor data quality (namely, a lack of psychophysiological data, where absence or presence is coded as 0 or 1). Given the pattern of anxiety from routine, desire for change, and a tendency to emotional instead of cognitive coping with uncertainty, with some indications of poor psychophysiological data, this factor was named “Restless Fidgeting”.

Third Factor: Steady Maximizing.

The third factor accounted for 12.3% of the variance within the rotated solution, with an initial, unrotated eigenvalue of 1.56. The third factor seems to capture a preference for maximal choices in stressful decision-scenarios, a tendency to low emotionality and a low cognitive coping in response to uncertainty, with some endorsement of anxiety from physical danger. This factor appears to account for a pattern

of little effect from uncertainty, a desire for choices, and sensitivity to situations of physical danger. There is a ‘pragmatic military’ or ‘prudent huntsman’ impression to this mentality; it received the name “Steady Maximizing”.

Fourth factor: Obedient Understanding.

The fourth factor accounted for 11.4% of the variance within the rotated solution, with an initial unrotated eigenvalue of 1.02. The fourth factor seems to capture a combination of cognitive ability and good quality data, with indications of lower desire for control and lower anxiety from physical danger. This factor, accounting for the least variance among the factors, was named “Obedient Understanding”.

Main Analysis

The results for the GLM analysis using a Repeated Measures MANOVA design with a 3 x 2 fully factorial table of experimental cell conditions (*Cc2*, *Cc4*, *Nc2*, *Nc4*, *Nn2*, *Nn4*) are reported below. Covariates were the first three sets of factor scores from the factor analysis of psychometric instruments described in Preliminary Analyses above. Dependent variables were maximum and minimum heart rate (HRACC, HRDEC), total peripheral resistance (TPR), decision-making time (RT1), and per-trial stress rating (STRSS).

Main effects and interaction.

A significant main effect was observed for both Choice Structure and Element Set Size. A significant interaction between Element Set Size and Choice Structure was also observed. A significant interaction was also found between Choice Structure and the set of factor scores from the third factor in the psychometric profiles, “Steady Maximizing”.

Choice Structure main effect.

The main effect of the Choice Structure was significant, Wilks' $\lambda = .30$, $F(10, 152) = 9.24$, $p < .001$, $\eta_p^2 = .45$ (univariate tests on Choice Structure and its interactions use Huynh-Feldt adjustments for non-sphericity throughout). The *Nc* condition (HRDEC for *Nc*, $M = 4.78$) exhibited lower mean heart rate minimums than the *Cc* condition (HRDEC for *Cc*, $M = 6.47$; mean difference $Cc-Nc = 1.71$, $t(48) = 3.03$, $p = 0.004$, Cohen's $d_z = 0.44$, 'moderate' effect size) and the *Nn* condition (HRDEC for *Nn*, $M = 6.90$; mean difference $Nc-Nn = -2.12$, $t(48) = -3.10$, $p = 0.003$, Cohen's $d_z = 0.45$, 'moderate' effect size). The *Cc* and *Nn* conditions did not differ from each other (HRDEC mean difference $Cc-Nn = -.41$, $t(48) = -1.11$, *n.s.*, Cohen's $d_z = 0.16$, no significant effect). Cohen's d_z is used here for effect size in a repeated measures design (Rosenthal, 1991, as cited in Lakens, 2013). In terms of decisional control available, there appears to be a pattern of more focus in the middle (*Nc*), as compared with reduced concentration (higher HRDEC) at the highest and lowest control levels (*Cc*, *Nn*).

Element Set Size main effect.

The main effect of Element Set Size was significant, Wilks' $\lambda = .60$, $F(5, 36) = 4.87$, $p = .002$, $\eta_p^2 = .40$. As expected, a greater Element Set Size resulted in higher values for lowest recorded heart rate (HRDEC). The value for HRDEC was significantly higher when Element Set Size was four ($q = 4$) than when Element Set Size was two ($q = 2$). The univariate results for HRDEC are $F(1, 40) = 6.64$, $p = .014$, $\eta_p^2 = .14$. Element Set Size might be expected to present more of a challenge with more elements, but HRDEC is expected to decrease with more information intake. Results indicate a kind of

‘selection’ is occurring, whereby participants are exhibiting more information intake when there is less information. This point is developed under Theoretical Synthesis in the Discussion. The Element Set Size main effect is also detected in part by Decision-Time (RT1) and Stress Rating (STRSS), according to univariate results (RT1, $F(1,40) = 14.18$, $p = .001$, $\eta_p^2 = .26$; STRSS, $F(1, 40) = 16.99$, $p < .001$, $\eta_p^2 = .30$). In contrast to HRDEC, RT1 and STRSS decrease from Element Set Size ($q = 2$) to Element Set Size ($q = 4$).

Choice Structure and Element Set Size interaction.

The interaction of Choice Structure and Element Set Size was significant, Wilks’ $\lambda = .73$, $F(10, 152) = 2.62$, $p = .006$, $\eta_p^2 = .15$. Dissection of this interaction revealed a steeper slope between Cc4 and Nc4 than between Cc2 and Nc2 for both Decision-Making time (RT1) and Stress Rating (STRSS). In univariate follow-up testing, RT1 and STRSS showed a significant result for a Choice Structure by Element Set Size interaction (RT1, $F(2, 80) = 9.98$, $p < .001$, $\eta_p^2 = .20$; STRSS, $F(2, 80) = 6.99$, $p = .002$, $\eta_p^2 = .15$). The other three dependent variables exhibited no significant univariate effect (HRACC, HRDEC, and TPR). Estimated Marginal Means patterns are depicted below (Figures 3.1, 3.2, and 3.3), with covariates fixed at their mean value (Anxious Abdicating = $-.037$, Restless Fidgeting = $-.175$, Steady Maximizing = $-.055$).

Figure 3.1 Estimated Marginal Means for RT1 in Choice x Elements Interaction

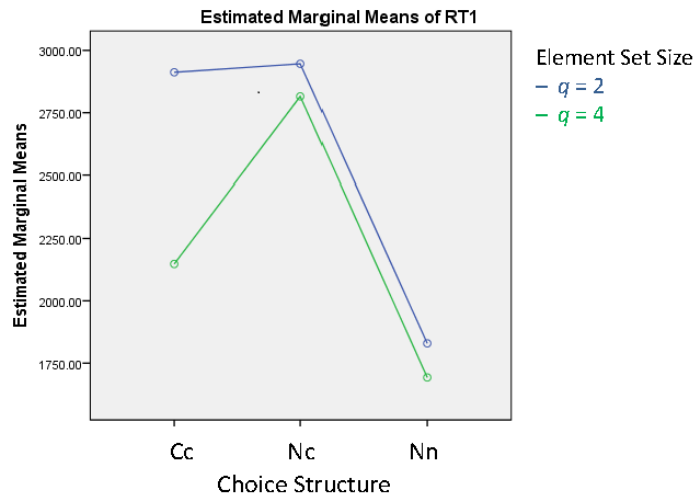


Figure 3.1. Decision-making time, RT1, pattern across six experimental cell conditions.

Figure 3.2 Estimated Marginal Means for Stress in Choice x Elements Interaction

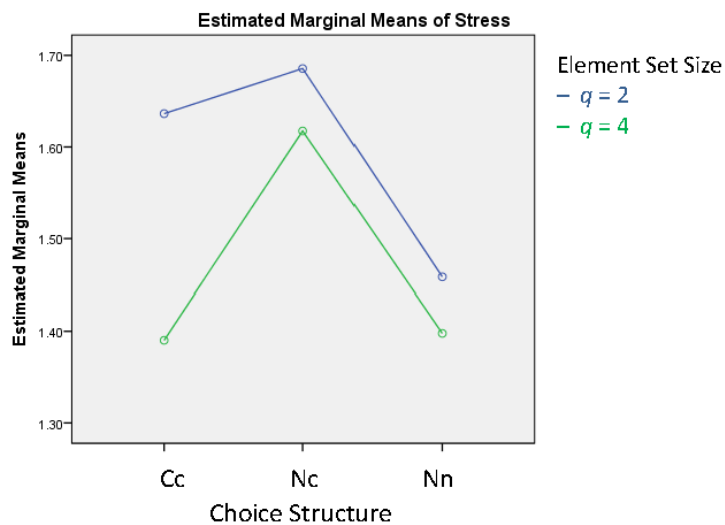


Figure 3.2. Single-Trial Rating of Subjective Stress, STRSS, across cell conditions.

Figure 3.3 Estimated Marginal Means for HRDEC in Choice x Elements Interaction

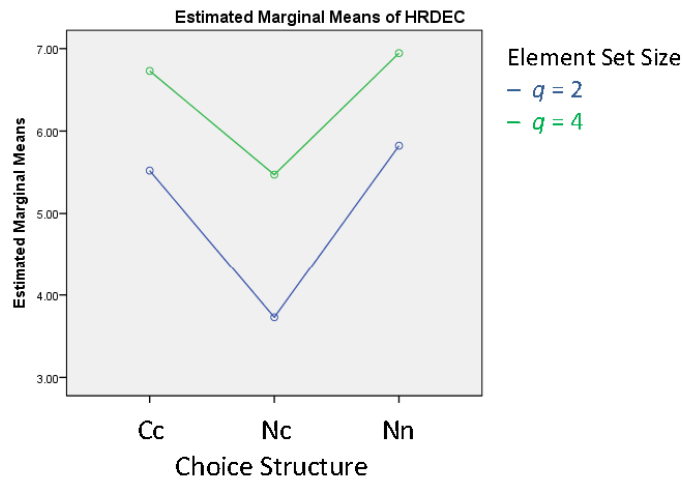


Figure 3.3. Minimum Heart Rate, HRDEC, across experimental cell conditions.

Covariate interaction of Choice Structure and Steady Maximizing factor score.

A significant interaction emerged between Choice Structure and factors scores for the “Steady Maximizing” factor, Wilks’ $\lambda = .73$, $F(10, 152) = 2.58$, $p = .007$, $\eta_p^2 = 15$.

This interaction expressed a significant trend whereby higher scores on the “Steady Maximizing” factor related to higher reported stress levels when engaging scenarios with intermediate levels of decisional control contexts ($Nc4$, $Cc2$), followed by an intermediate amount of stress in extreme decisional control contexts (very little control, $Nc2$, or very much control, $Cc4$), and lastly, participants high on “Steady Maximizing” reported the least stress in scenarios with no decisional control ($Nn4$, $Nn2$). Participants with a higher maximizing preference appear to experience the most subjective stress in

intermediate control scenarios. One explanation might be that this engages the most effort on their part, hence creating a memory of exertion, or stress.

Among the two independent variables, Choice Structure and Element Set Size, the three sets of covariate factor scores, “Anxious Abdicating”, “Restless Fidgeting”, and “Steady Maximizing”, and the five dependent measures, heart rate acceleration, heart rate deceleration, total peripheral resistance, decision-making time, and per-trial stress ratings, no other significant effects were revealed. It can be noted that trends appear to suggest sensitivity to personality variables in the psychophysiological measures, but no further significant results emerged.

Confounds and Controls

Age, trial order, sex.

Correlation results for dependent variables of Maximum Heart Rate, Minimum Heart Rate, Total Peripheral Resistance, Decision-time and Stress Rating with Age, Trial Order, and Sex revealed only one significant correlation, between RT1 and Age, $r = 0.27$, $N = 65$, $p = .03$. This indicates that, to a weak-moderate degree, participant ages vary positively with reaction times. This single significant correlation is not considered an obstacle to validity of findings.

Baseline and Task values.

The same analyses as were conducted on reactivity scores were also conducted on Baseline scores only and Task scores only. Recall that Reactivity scores were calculated as ‘Task scores minus Baseline scores’. No significant results were found for Baseline scores for maximum heart rate, minimum heart rate, and total peripheral resistance with the same 3 x 2 MANOVA design as for Reactivity scores. For Task scores, the same 3 x

2 MANOVA design revealed significant main effects for Choice Structure (Wilks' $\lambda = .84$, $F(6, 172) = 2.59$, $p = .02$, $\eta_p^2 = .08$) and Element Set Size (Wilks' $\lambda = .82$, $F(3, 42) = 2.59$, $p = .02$, $\eta_p^2 = .08$), but no significant effect for an interaction or for any covariate interaction effects. This pattern of results supports the main results, and indicates no significant confounding from Baseline scores.

Overall, with regard to confounds and control variables, reactivity score main results are not reflected in the baseline scores results, but somewhat reflected in task score results. This is consistent with the assumption of a causal effect for the experimental manipulation, with added validation for the improved sensitivity of reactivity scores over task scores only.

Discussion

Addressing the Hypothesis

This study has allowed the examination of participant personality, behavior, and subjective experience as it relates to variations of nested-structure decision-making in stressful situations. The expectation of increased stress with reduced decisional control has been met, with an important qualification of a 'v-shaped' trend, not a strict linear progression. The expectation of increased stress with increased information processing has been met to some degree. An interaction of choice structure and number of elements in specified decisional control arrangements has been validated, with particular emphasis on the difference between the Cc and Nc conditions. Overall, this study strongly supports 1) the validity of the decisional control model a predictor of response to decision structures, 2) the effective relation of decisional control to reaction times, stress ratings,

and psychophysiological measurements, and 3) the utility of decisional control in providing a theoretical integration of otherwise potentially disparate results.

The detailed design, involved data collection and analysis, and extensive interpretation of results have arguably advanced the understanding of decision scenarios. The relative impact of decision scenario features (choice architecture, number of choices) on psychophysiological, reaction time, and subjective response data in the context of multi-dimensional psychometric profiles and model-driven theoretical expectations is supported as relevant and able to serve as a cohesive knowledge framework in stress and coping research.

Construct-validation results.

Choice Structure main effect.

Our first hypothesis was that Choice Structure (Cc , Nc , Nn) would have a significant impact on psychophysiological response. Research has been done in this area in terms of the impact of experimentally manipulated stress on psychophysiological variables (e.g., Blascovich, et al, 2004; Tomaka, Blascovich, et al., 1997), but the use of a decisional control paradigm as the independent variable for predicting differences in stress induction still decidedly novel. Recent work has extended the theoretical (Shanahan & Neufeld, 2010) and applied theoretical side of this approach (Levy, Yao, McGuire, Vollick, Jetté, Shanahan, Hay, & Neufeld, 2012). The decisional control model quantifies stimulus properties directly bearing on potential sources of stress, such as challenge-stress activation and associated individual differences. As such, several measures were considered for detecting experimental effects. Reactivity scores were used

as the principal dependent variable, calculated by subtracting psychophysiological readings taken during the Baseline period from the same readings during the Task completion.

Particular sensitivity for the decisional control conditions emerged for minimum heart rate, also called heart rate deceleration (HRDEC; Morrison, Neufeld & Lefebvre, 1988). Other measures used in previous formats showed little relation to the hypothesis of interest in preliminary analyses. Some indications exist for the relevance of maximum heart rate (HRACC), total peripheral resistance (TPR), and other measures such as stroke volume (SV), cardiac output (CO) and pre-ejection period (PEP) as contributing to discriminability of personality and cognition-related variables. Although these measures were examined, they do not appear in the present design and research sample to interact meaningfully with the hypotheses.

The main effect of Choice structure indicates a 'v-shape' if arranging levels sequentially as *Cc*, *Nc*, *Nn*. The pattern can be re-arranged in this order to form a linear progression: *Nc*, *Cc*, *Nn*. This yields a positive linear slope for minimum heart rate HRDEC, and a negative linear slope for decision-making time RT1 and single-trial rating of subjective stress STRSS. Although more decisional control is available at the *Cc* level, the present results suggest that participants gravitate to a type of 'bounded decision scenario'. As the prototype of a 'bounded decision scenario', empirical indicators of the exercise of decisional control suggest it is most engaged in the *Nc* condition, even though more decisional control available in the *Cc* condition. Not in dispute in this new interpretation is the existing model axiom that the *Nn* condition contains no opportunity for threat reduction through decision-making.

Element Set Size main effect.

The main effect of Element Set Size goes in a direction contrary to expectation, but instructively so. Minimum heart rate HRDEC goes up with Element Set Size. However, the correspondence of this *rise* with a *decrease* in Decision Time RT1 and Subjective Stress STRSS suggests lowered participant interest and concern with a larger number of items, even between Element Set Sizes in the *Nn* condition alone, where the difference in number of items might be considered ‘academic’. This suggests the consideration in future research of ‘decision-maker disengagement’ with an increasing number threat items.

Theoretical Synthesis

A bilateral formulation of value for decision-making.

Reversal in slope: A ‘v-shaped’ pattern.

In examining the pattern of values across choice structures, a ‘v-shaped’ or inverted ‘v-shaped’ pattern emerges for minimum heart rate, decision-making time and subjective stress rating, notwithstanding some degree of interaction. More formally stated, when arranging the three Choice Structures from left to right as *Cc*, *Nc*, and *Nn* there is a reversal of sign in the slope at the *Nc* Choice Structure (middle IV level) in each of RT1 (positive from *Cc* to *Nc*, negative from *Nc* to *Nn*), STRSS (same as RT1), and HRDEC (negative from *Cc* to *Nc*, positive from *Nc* to *Nn*). Accessing the theoretical and experimental paradigm accounting for the cost and expenditure of stress, an integration of these two related patterns (‘v’ and ‘inverted v’) across three modalities (psychophysiological, reaction time, and subjective ratings) into of a model-based unity is reported below.

In examining the ‘v-shape’ and the inverted ‘v-shape’, the idea of one latent quantity cresting as a second latent quantity decreases becomes apparent. In combination, two latent linear patterns acting together can be reflected in a ‘v-shape’ on a dependent measure. In examining the values generated from *a priori* quantities within the decisional control model, there are two candidate trends within the modeled quantities across the Cc , Nc , Nn choice structures that increase and decrease in converse fashion. Namely, at the Cc level where decisional control (related to RSS and $Pr(t_1)$) is highest, expectation of threat ($E(t)$, in the wake of implementing available decisional control) is lowest. The converse also holds at the Nn level: where decisional control is lowest, highest post-scenario expectation of threat prevails.

An ‘economy of probabilistic stress’.

If either minimizing threat or minimizing efforts at control were unilaterally salient to the decision-maker, then either Cc or Nn , respectively, should be unequivocally preferred. However, participant “focus” (operationalized below as amount of decrease in minimum heart rate, varying inversely with $HRDEC$), decision-making time (reaction time allotted to information processing), and subjective report of stress (subjective experience of increased arousal and task demand) all crest “in the middle” at the Nc condition. This pattern points to some combination of the expenditure of mental effort and the psychophysiological cost of exposure to threat as helping to determine the degree of participant investment in negotiating a given decision scenario. The concept of competing desirable quantities has been present since the inception of the decisional control model, as a ratio between stress and counter-stress activity (Neufeld, 1982), an

“economy of probabilistic stress” (Morrison, Neufeld, & Lefebvre, 1988), and “the ‘costs’ of coping” (Benn, 1992).

Use of the ‘modus’: method-driven data.

Extensive modeling work has been done both on formulations for mathematical expectancies and exploration of model properties through large-scale simulation (Shanahan & Neufeld, 2010; Shanahan, Nguyen, & Neufeld, 2012). As a result of this work, the prospect of using ‘modus’ data, or ‘method-data’ as a principled predictor of experimental values is feasible. This type of data, when generated by theoretical formulation, can create an extensive set of expectancies that become so numerous as to warrant their treatment in some ways as data. Being theoretically-based however, they are more like a very large number of inter-linked predictions. Using these as the detailed and intricate theoretical expectancy for experimental results allows for a more robust test of the model, and of the underlying assumptions. Given so many ‘working parts’, even partial confirmation of expectancies will confer support to model design validity.

Psychological meaning and relations between model quantities.

The quantities of response set size RSS and probability of access to the least threatening option $Pr(t_1)$ can be used as indicators of information processing demand (cognition) and available threat reduction (control), respectively. These are perfectly correlated, but RSS can be considered a more discrete index of cost of cognition, reflecting directly the whole positive number of items to evaluate. The $Pr(t_1)$ measure can be considered an index of degree of control attendant to a specific decision structure, because it is calculated as the number of items to evaluate as a fraction of the entire range of potential threat items, specifically $Pr(t_1) = RSS / pq$.

More relevant for comparisons to be made with $E(t)$, $Pr(t_1)$ is a proportion, like $E(t)$, whereas RSS is a count of a discrete number of items. Although RSS and $Pr(t_1)$ vary together, these two types of quantities (positive whole numbers and proportions) exhibit different properties, for example in their upper limit (unlimited for RSS , 1.0 for $Pr(t_1)$). A concomitant feature of 'control' is a global or comprehensive perspective of the situation within which control is exercised. As a proportional value, $Pr(t_1)$ has an implied upper limit of 1.0, and tends to conform as a measure to an index of 'control' (a value in larger context). By contrast, cognitive work in this case aligns with the individual items and with RSS as the constituent evaluation of options rather than a situationally-relative assessment, or again, as raw number of cognitive operations and the effort involved in completing mental work, rather than constituent evaluations in proportion to all evaluations.

The quantity of cumulative expectation of threat $E(t)$ remaining (after implementation of available decisional control) can be used as an indicator of the magnitude of threat that will remain to be faced after information processing demands are fulfilled. This is a kind of 'pay-off' marker', indexed to investment of cognitive and coping costs. More generally, it is an indicator of the threat-exposure that will remain after the decisional-control scenario is negotiated. The reduction of $E(t)$ acts as a reward for increased cognition, specifically engagement of RSS and its information processing demands. A higher $E(t)$ typically reflects low-level cognitive demands and coping expenditure (exercise of control), namely a lower RSS and lower $Pr(t_1)$.

Two sources of ‘stress cost’ to the decision-maker.

A further element of this theoretical synthesis specifies the calculation of the two sources of ‘stress cost’: cognitive effort and threat exposure. Cognitive cost relates RSS and $E(t)$ as a fraction, where the quotient indicates the cognitive cost in terms of mental effort of RSS per unit of post-decisional $E(t)$. For its part, threat-exposure $E(t)$ after the exercise of decisional control is divided by the amount of decisional control $Pr(t_1)$ afforded by or characteristic of the scenario, and can be considered the threat-exposure requirement that is accepted by the participant in exchange for a certain degree of control, or the concomitant of control, responsibility.

Another, way to conceptualize these two quantities is, first, anchoring $E(t)$ as the denominator with RSS pivoting around it in the numerator: “How valuable is the thinking I will have to do (information processing per unit of threat-exposure)?” ($RSS / E(t)$). Second, $Pr(t_1)$ acts as the anchor with $E(t)$ pivoting around it in the numerator: “How much risk am I exposed to in exchange for my thinking responsibility (threat-exposure per unit of control)?” ($E(t) / Pr(t_1)$).

Tabular illustration of procedure for obtaining Decision Value.

In Table 5, primary quantities from theoretical considerations described above are listed, with the relevant dependent measures that successfully discriminate expected main effects and interaction of Choice Structure and Element Set Size. In Table 6, and 7, below, the theoretical prediction and empirical measures can be rendered comparable by standardizing them across all measurements proper to their own quantity throughout the 3 x 2 experimental condition levels.

Table 5

Relevant quantities for comparison between model-driven and empirically measured data

Quantity	Quantity Abbreviations	$Cc2$	$Cc4$	$Nc2$	$Nc4$	$Nn2$	$Nn4$
Response Set Size	RSS^*	4	8	2	4	1	1
Prob. Access to t_1	$Pr(t_1)^*$	1.00	1.00	.500	.500	.250	.125
Expected threat	$E(t)^*$.300	.300	.400	.351	.525	.525
Min. H.R. - Reactivity	HRDEC	5.79	7.19	3.79	5.78	5.98	7.82
Decision-making Time	RT1	2814.6	2094.9	2865.5	2664.6	1712.4	1675.6
Subjective Stress	STRSS	1.60	1.43	1.64	1.61	1.39	1.39

* Calculated as in Shanahan & Neufeld (2010); Shanahan, Nguyen, & Neufeld (2012).

Examining Table 5, relative increase and decrease can be observed in converse patterns in both the modeled and experimental quantities. Information processing demand, represented in the RSS measure, tends to decrease moving towards the right in Table 5. Decisional control $Pr(t_1)$ decreases similarly. Expectation of threat $E(t)$, for its part, tends to increase moving to the right in Table 5 as the decision-maker has less decisional control and must face an increasingly random assignment of threat values. Note that in Table 5 above, $t_1 = 0.30$ and $t_{max} = 0.75$ for both the model and experiment quantities. Intervals in the model calculations are evenly spaced according to a full set of element values (t_1 to t_4 for $q = 2$, t_1 to t_8 for $q = 4$). The selection has been done for these hypothetical values to obtain $E(t)$ values, following *maximax* and other model assumptions, stated above in the introductory section.

Observable in Table 5, also, is a decrease and then an increase across HRDEC, left to right, and an increase and decrease in both RT1 and STRSS. Quantities are scaled in different units, however, and thus not immediately comparable. The quotients mentioned earlier are presented in Table 6 below.

Table 6

Quotients for Costs of Cognition and Threat-Exposure by Experimental Condition

Quantity	Quantity Short form	<i>Cc2</i>	<i>Cc4</i>	<i>Nc2</i>	<i>Nc4</i>	<i>Nn2</i>	<i>Nn4</i>
RSS Items per Unit-Threat	$RSS/E(t)$	13.33	26.67	5.00	11.38	1.90	1.90
$E(t)$ Threat per Unit-Control	$E(t)/Pr(t_1)$	0.300	0.300	0.800	0.703	2.100	4.200

In Table 7 below, the values in Table 6 are made proportional across the sum of quantity values in each condition, in order to make quantities comparable. This proportional approach results in a sum of 1.0 across the six experimental conditions for both of the two ‘cost’ quantities, and each value can also be thought of as a percentage of the sum total across all six cells, such that proportion of information processing demand $IPDp = [RSS/E(t)]/\sum[RSS/E(t)]$ and proportion of threat-exposure $TEp = [E(t)/Pr(t_1)]/\sum[E(t)/Pr(t_1)]$. Note that the denominator terms in the two equations above function as a kind of normalizing factor, contextualizing the individual cell condition value in terms of the aggregate value across comparable cells.

Also in Table 7 below, the proportion of information processing demand ($IPDp$) and the proportion threat-exposure (TEp) are averaged. This results in a theoretical account of relative threat from two sources, information processing and exposure to threat, apportioned across the six experimental conditions. This sum is named Threat-Control Expenditure, as it is the required ‘expenditure’ from the participant to exercise control and minimize threat.

One further quantity is listed in Table 7, Decision Value. In what appears to be a promising approach to two-source decision stress, Decision Value is the inverse of the Threat-Control Expenditure (proportion), and they vary as perfect negative correlates. The inversion procedure used is akin to a 180 degree rotation of the graph that would depict Threat-Control Expenditure – Decision Value is Threat-Control Expenditure

“upside down” (see procedure explanation below Table 8). Substantively, Threat-Control Expenditure represents the combination of cost of cognition for threat-reduction and the cost of threat-exposure for control, after the exercise of maximax-driven decisional control in the scenario. This value is at a maximum for the $Nn4$ condition in Table 7, and this condition may be considered the ‘most expensive’ when considering cognition and threat-exposure. Decision Value is the perfect inverse of the Threat-Control Expenditure proportion (TEp), and is at a maximum at $Nc2$; this appears to be the ‘best value for combined cognition and threat-exposure’. This metric has identified, through theoretically available quantities and theoretically meaningful calculations, a feasible distribution of relative preference. Depicted further below (Table 9), the empirical measurements of minimum heart rate, time of decision-making, and stress rating attest to this pattern of preference as reflecting the tendencies of participant decision-making in our sample.

Table 7

Proportional Quantities and Averaged Effort Cost for Cognition and Threat-Exposure

Quantity	Quantity Short form	$Cc2$	$Cc4$	$Nc2$	$Nc4$	$Nn2$	$Nn4$
Info. Processing Demand	$IPDp$.2215	.4430	.0831	.1891	.0316	.0316
Threat Exposure	TEp	.0357	.0357	.0952	.0836	.2499	.4998
Threat-Control Expenditure	$(IPDp + TEp)/2$.1286	.2394	.0891	.1364	.1408	.2657
Decision Value	$[(IPDp + TEp)/2]inv$.2047	.0940	.2442	.1970	.1926	.0676

In Table 7, above, the most ‘information processing demand’ $IPDp$, or, proportionalized $RSS/E(t)$, is located in $Cc4$, $Cc2$, and $Nc4$. The most ‘threat-exposure’ is found in the Nn conditions. Averaging these proportions and weighting them equally as sources of stress results in a specific allocation of stress expectation for each experimental condition, Threat-Control Expenditure. The inverse of this list of

proportions may be considered to reflect the amount of ‘threat-control’ obtained for the investment of decision resources (information processing and threat-exposure). This proportional quantity is termed Decision Value, as above in Table 7.

Table 8

Proportional Allotment of Empirically-Measured Quantities, with Respective Inverse

Quantity	Quantity Short form	<i>Cc2</i>	<i>Cc4</i>	<i>Nc2</i>	<i>Nc4</i>	<i>Nn2</i>	<i>Nn4</i>
Distraction	HRDECp	.1593	.1978	.1042	.1589	.1646	.2152
Attention	RT1p	.2036	.1515	.2072	.1927	.1238	.1212
Effort	STRSSp	.1764	.1572	.1812	.1778	.1538	.1535
Calming Focus	HRDECp-inv	.1741	.1355	.2292	.1744	.1687	.1182
Task Avoidance	RT1p-inv	.1298	.1818	.1261	.1406	.2095	.2122
Task Aversion	STRSSp-inv	.1569	.1761	.1521	.1555	.1795	.1798

The values in Table 8 above report the relative apportioning within a given variable of the quantity represented by the proportionalized empirical quantities of HRDECp, RT1p and STRSSp, as well as the inverse of their proportional quantities, HRDECp-inv, RT1p-inv and STRSSp-inv. The highest relative minimum heart rate reactivity occurs in the *Nn* conditions, and somewhat in the *Cc4* condition. The lowest heart rate deceleration occurs in the *Nc2* condition.

Inversion procedure example for HRDECp and HRDECp-inv: ‘Calming Focus’.

Presented in Table 8 is also the inverse proportion of heart rate deceleration, HRDECp-inv. This preserves a full summation value of one, and variance properties. ‘Calming Focus’ HRDECp-inv is the inverse of HRDECp, calculated as a ‘flip’ or by subtracting HRDECp proportional values from a value of 1. If a graph of HRDECp were produced, HRDECp-inv is already depicted, but is *upside down*. The inverting transformation of HRDECp reflects relative variation in the data according to a construct involving a type of effortful, physiologically de-arousing but cognitively-intensifying

focus. This would appear to be analogous to the physiological calming that biathletes must make to their heart rate as they increase their mental focus for the marksmanship component required between Nordic skiing intervals on their course. This measure, to be called ‘Calming Focus’ for HRDECp-inv, varies positively with an increase in information intake and in perception of taxing effort, as seen in similar variation in decision-time and subjective stress.

Derivation of ‘Task Avoidance’ RT1p-inv and ‘Task Aversion’ STRSSp-inv.

Similarly to HRDECp and HRDECp-inv, the inverse for RT1p is termed “Task Avoidance” RT1p-inv, in that as time of cognition on a given decisional scenario decrease, task avoidance can be considered to increase. The inverse for STRSSp, labeled STRSSp-inv reflects decreased experience of subjective stress. This has been termed Task Aversion. Although stress is typically considered *undesirable*, the behavioral evidence in our experiment is that subjective stress is highest when the most time and most focus is given to a decisional scenario. As such, the *effort furnished* is another conception that follows the stress experienced. Despite the usually undesirable aspect of experiencing stress (cf., Lazarus & Launier, 1978), nonetheless, where investment of effort is to some degree voluntary, it appears to be most invested where perceived reward is most worth the invested effort. As such “Task Aversion” and “Task Attraction” are counterpoised as directly related to “Low Stress” and “High Stress” in this context. Stress appears to be rated more highly in scenarios where effort is perceived as worthwhile. As such, the interpretation of the inverse of the proportional Stress value (STRSSp-inv) is that it increases with Task Aversion, or, with ‘disinterest in furnishing an effort’ (notably in the *Nn* conditions).

Threat-Control Expenditure and its inverse, Decision Value.

In Table 9, below, an ordered arrangement and contrast is made for the same allotment of data with two perfectly inverse measures. The Threat-Control Expenditure varies with Distraction, Avoidance, and Disinterest, and the Decision Value varies with Focus, Time, and Effort. These are not independent patterns, but perfect complements with opposite variation: hopefully the result is an enlightening juxtaposition of psychologically substantive labels with a quantitative interpretation.

Table 9

Threat-Control Expenditure, Decision Value and Related Empirical Proportions

Quantity	Abbrev.	Cc2	Cc4	Nc2	Nc4	Nn2	Nn4
Threat-Control Expenditure	<i>IPDp+TEp</i>	.1286	.2394	.0891	.1364	.1408	.2657
Distraction	HRDECp	.1593	.1978	.1042	.1590	.1646	.2152
Avoidance	RT1p-inv	.1298	.1818	.1261	.1406	.2095	.2122
Disinterest	STRSSp-inv	.1569	.1761	.1521	.1555	.1795	.1798
Decision Value	<i>(IPDp+TEp)inv</i>	.2047	.0940	.2442	.1970	.1926	.0676
Focus	HRDECp-inv	.1741	.1355	.2292	.1744	.1687	.1182
Attention	RT1p	.2036	.1515	.2072	.1927	.1238	.1212
Effort	STRSSp	.1764	.1572	.1812	.1778	.1538	.1535

Finally, to illustrate the cohesiveness of the pattern of results in Table 9, Figure 4.1 below depicts the quantities in the six experimental conditions ordered according to Decision Value, as theoretically-determined above. With this new theoretical approach, it appears that for predicting the ordering of participant preference for effort expenditure, the Decision Value calculation offers a correct, ‘unscrambled’ order for the decisional control scenarios that matches data patterns in our study. The six experimental conditions have been ordered according to the theoretical quantity of Decision Value, lowest to highest. This ‘untangling’ was suggested by empirical findings, but has been applied by the valid technique of ‘abductive reasoning’ (see first component document in

this dissertation, Shanahan, Townsend, & Neufeld, 2015), the use of *a priori* quantities in theoretical re-formulation. The particular value of this method is that because it is done with *a priori* model-specified quantities, it can be applied predictively in future for the decisional control experiments to the same quantities in the design.

Figure 4.1 Decision Structure by Decision Value, with STRSSp, RT1p, and HRDECp-inv

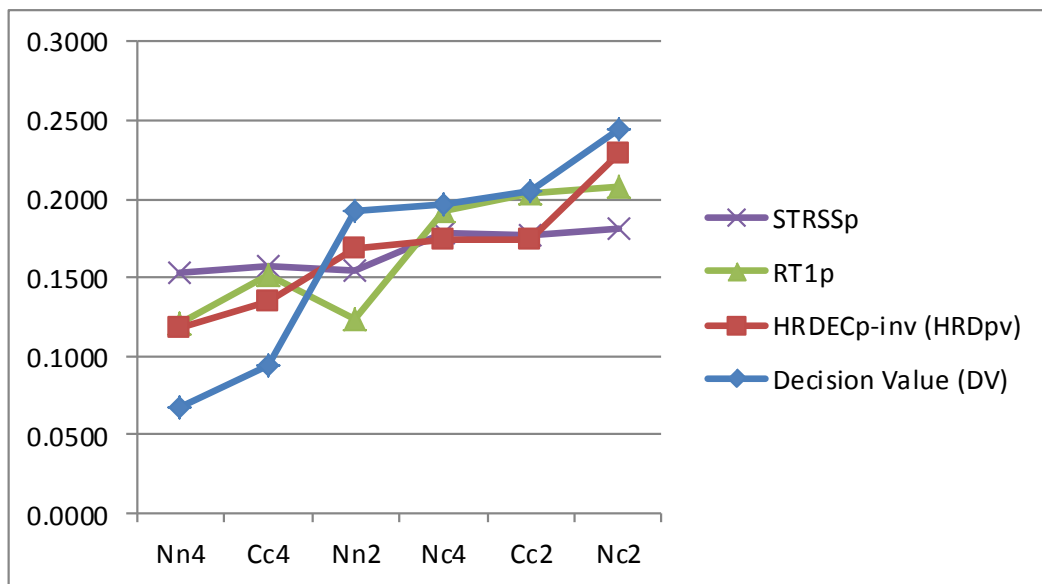


Figure 4.1. Proportionalized values for Decision Value, HRDECp-inv, (index of focus), RT1p (time of decision-making cognition), and STRSSp (expenditure of effort). Quantities have been proportionalized across 3 x 2 experimental conditions: the sum of all six values on a line is 1.0.

Figure 4.2 Cumulative Decision Value, STRSSp, RT1p, and HRDECp-inv, by Scenario

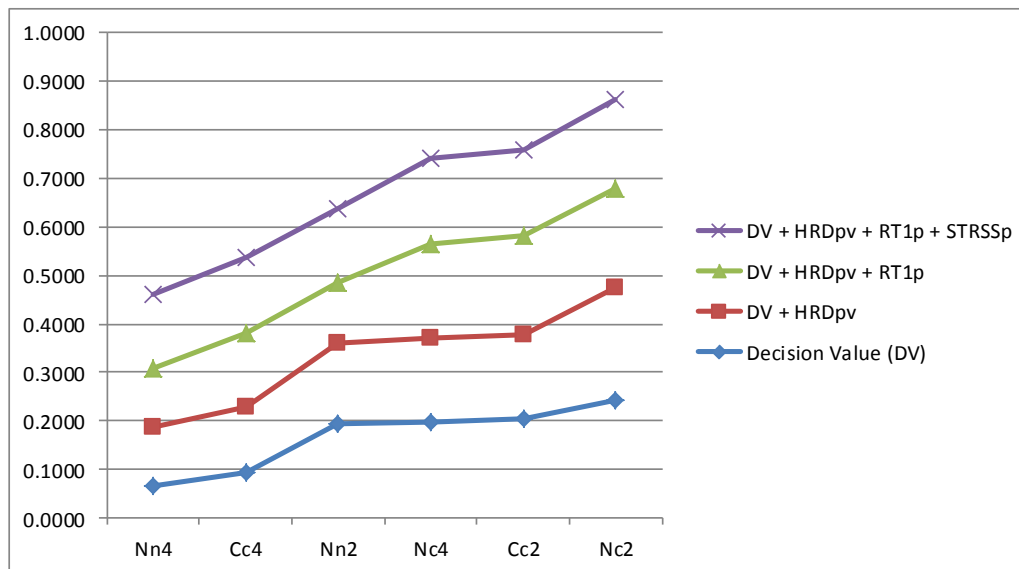


Figure 4.2. Progression of Decision Value, HRDECp-inv, RT1p and STRSSp values, largely parallel, cumulatively depicting the same values as Figure 4.1; line-point at each cell condition level is a sum of measures, as in the legend, starting with Decision Value.

Commenting on Figures 4.1 and 4.2, what is intended as the principal highlight in the arrangements chosen is the emphasis on the parallel nature of the progression across the experimental cell conditions re-arranged according to the theoretically-generated Decision Value in each decisional control scenario level. Expressed as Decision Value only (blue diamond line in Figure 4.1 and 4.2), the calculation has no empirical relevance. Reflected in Minimum Heart Rate patterns (red square lines), a useful link is established to an empirically measurable quantity as indicative of changes in Decision Value. Reflected in both Minimum Heart Rate and Decision-Making Time (green triangle lines), both psychophysiological and quantitative behavioral indices now mirror the inherent theoretical property of decision value. Finally, the conscious experience of the decision-maker, as reported in subjective stress ratings (purple 'x' lines). Thus, the

subjective experience, indicated by stress ratings, the practical behavior, as indicated by duration of decision-making, and the psychophysiological reaction in minimum per-trial heart rate *all act in concert with decision value expectations*, a purely theoretical measure. An important new insight is potentially revealed in this analysis. Mindful not to overstate the case, the prospect nonetheless exists that with replication and extension, this study might serve as a type of ‘Rosetta Stone’ for research on stress and decision-making.

Correlational validation.

Finally, the condition averages and the theoretical Decision Value align at a high or very high correlation level. The cell condition averages (*Cc2, Cc4, Nc2, Nc4, Nn2, Nn4*) correlate to the following degree with RT1, STRSS, and the task values for HRDEC, labelled HRDECt. The task values for HRDEC were used in a correlational analysis of raw data values, because they are comparable to the RT1 and STRSS scores in relating direct empirical quantities, and not difference scores as the reactivity score calculation requires.

Correlations are reported as pseudo- R^2 because they are correlations between theoretical predictions and averaged values; as such, correlations should be taken as indications of relation between the fundamental patterns within the respective measures, but cannot be strictly interpreted in the same sense as bivariate correlations between two raw data samples. The correlations emerged as follows: Decision Value and RT1, pseudo- $R^2 = .72$, $N = 6$, $p = .053$ (one-tailed), Decision Value and STRSS, pseudo- $R^2 = .77$, $N = 6$, $p = .037$ (one-tailed), and Decision Value and HRDECt, pseudo- $R^2 = -.92$, $N = 6$, $p = 0.005$ (one-tailed). The pseudo- R^2 values (cf., Cobb, 1981; Jammernegg &

Fischer, 1986), again, are used because they are linking a set of highly involved theoretical calculations and sets of highly aggregated empirical values.

It appears that the single Decision Value theoretical calculation is a novel and potentially valuable positive predictor of variation in average time spent in a decisional control scenario (RT1), of subjective stress in a decisional control scenario (STRSS), and a very powerful negative predictor of minimum heart rate during task completion (HRDEct, not a reactivity score in this case).³

Bilateral appraisal of inherent decision value.

The use of proportion for comparing experimental conditions of decisional control ‘quantities’, and the application of the analogous procedures on scores representing experimental indices of information processing, production of individual effort, and calm for increased concentration reveals a potentially valuable connection to model predictions. With the inverse of the proportionalized data adjusting for opposite direction of variation and relative distribution across experimental cell conditions, the time of processing, effort, and focus of participants can be depicted as functioning in parallel to

³ The task values for minimum heart rate were used for the condition averages because it maintains raw values that are all of the same sign (positive valence). Where sign differs in reactivity scores (some positive, some negative), calculation of valid proportions becomes complex.

the bilaterally-derived perception of value of given decisional scenarios assembled from inherent properties of the decision scenarios.

In this sense, a candidate principle behind the two kinds of ‘currency’ in Morrison, Neufeld and Lefebvre’s ‘economy of probabilistic stress’ (1988) have been identified: the information processing exchanged per unit of eventual threat to be faced, and the amount of scenario-dependent ultimate threat-exposure per unit of decisional control afforded in that particular scenario. Using these two ‘currencies’, the value of a given decision scenario’s properties appears to be acted on by the participants in a pattern that reflects a comparable premium (similar weighting) both for reduced information processing and for reduced threat-exposure. Adding these two ‘costs’ with equal weighting, Nc^2 that emerges as the best value for what participants evidently perceive as the investment required to negotiate a decision scenario in order to get best returns, namely, the least information processing for the most threat reduction. The sequencing of the six experimental conditions according to Decision Value, yields a parallel progression for the theoretically-derived decision value and empirically-derived proportions for decision time (time of decision-making cognition), decision effort (per-trial self-report of subjective stress), and decision focus (information intake, a decrease in minimum heart rate) as seen in Figure 4.2.

Decision-Making Style: Maximizing, Satisficing, Simplifying

Although presented more extensively in other contexts (Shanahan, Pawluk, Hong, & Neufeld, 2012), the information processing proclivities of participants has registered a significant interaction with Choice Structure. This represents a vindication for the

Maximizing score as a driving variable in the interacting covariate factor “Steady Maximizing” (factor loading: 0.79), with the more detailed pattern suggesting that participants high on maximizing show longer decision time and report most stress in intermediate decisional control scenarios (*Nc4*, *Cc2*), less so in scenarios of highest or lowest decisional control (*Cc4*, *Nc2*), and least in situations of no decisional control (*Nn4*, *Nn2*). As a validity consideration, it can be noted, as earlier in this document, that threat levels were evenly distributed in the sample, both in the theoretical derivations and within the experimentally presented threat options. This ‘attraction of effort’ (indicated by higher stress reports) on some of the best decision value conditions (*Nc4*, and *Cc2*, for example) by participants who tend to score higher on Maximizing is consistent with payoff for good decision-making in these conditions and what would be expected as reflecting an individual preference for ‘maximizing’ in decision-making.

Future Investigations

Validation work is an enticing prospect for this type of approach. The pattern of results found in the present study can potentially inform a variety of new experimental programs. In particular, the metric developed for Decision Value works very well in describing empirical results within the present dataset. Other metrics like it could inform future work with the various data types used in this study. The decision value is derived entirely from the structural properties of the decision scenarios, and as such is open to deliberate, purposeful manipulation and prediction for future investigations. Even the discovery of attenuation of this effect would advance stress and decision-making science, because of the formal decisional-control specifications backdrop.

More immediately, analysis of a second data set designed with the same quantities and decisional control model paradigm has revealed that replication is not easily obtained. This dataset provides the basis for an independent test of these calculations. A list of expected 'threat-control expenditure' by scenario for this experiment has been generated and, within a limited context of comparison, did not replicate results.

Limitations

Study limitations include standard challenges in the use of psychophysiological variables. Within the analyses, some results for HRACC and TPR approached or met marginal significance ($p < .10$), but a more developed theoretical approach to their specific action in decision contexts will help in testing for effects not detected, or detectable, in the current study. This new round of testing could involve *a priori* work suggested by the current decision value approach.

Several types of data were incorporated within this study. Their successful integration is a testament to the value of formal modeling of psychologically meaningful quantities. Further research would nonetheless likely benefit from some 'specialization' research in model properties investigated, targeting specific modalities to refine techniques and methods conferring greater sensitivity to decisional control quantities. After such refinements, new 'integrative' studies like our own would again be in order. Although detailed and methodical, our study has an exploratory and inaugural character.

Finally, a limitation of this study was attritional loss of about 16 psychophysiological sets of readings, across the full range of 65 eligible participants. This affected power in the analyses involving psychophysiological readings. Even with

the use of the state-of-the-art technology and methodology (e.g., Blascovich, 2008; Blascovich et al., 2004), this can be somewhat expected in a psychophysiological research context. Future examiners do well to practice electrode application and monitor results throughout data collection. Individual adaptations may emerge as to optimal placement of electrodes for certain common individual differences within participant samples.

Conclusions

As observed by their impact on psychophysiological variables, quantities reflecting decisional control constructs are confirmed as informative. There appears to be a strong influence of element set size, or, number of choices, on the stress reaction in participants. There also are indications of a “v-shaped” pattern of variation, whereby the stress responses of participants to full free choice or to no free choice at all are more similar to each other as experimental conditions than they are to the ‘mixed choice’ situation of Nc , composed of super-ordinate external assignment (N) and subordinate choice (C). Finally, the specific calculation of decision value, as highly predictive of time of decision-making cognition, subjective stress, and decrease in minimum heart rate, is potentially of value for research in the decisional control paradigm.

Deep structure modeling of theoretical quantities can permit a much-improved grasp in understanding human perception of interlocking and reciprocal constructs. Reduced information processing demand for maximum threat reduction are confirmed by reaction time, psychophysiological, and subjective ratings data to represent competing but interdependent interests for the human decision-maker.

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4.3 Comment: “Information Processing (...)”

The refreshing result in the paper presented above is that the decisional control model does indeed affect the decision-making of regular human participants, in concert with extensive work in the theoretical and simulation domains. With such an intricate degree of modeling, it is inevitable that in some aspects, under certain conditions, the model will hold to a greater or lesser degree, as the operative mechanisms can and will vary depending on the context and independent variable levels.

The proximate study, reported in Chapter 5, details a considerable research effort to map out those variable confluence zones, model assumptions, and other model-prescribed phenomena that affect the degree to which model expectations hold or do not. This, in turn, informs a more general appreciation of the decision-making phenomena under study, and suggests where other important influences may come in to affect decision-maker behavior.

4.4 Ethics for “Information Processing (...)”

Note that this project was conducted as a subset of research in the ethics submission entitled “Coping with stress through decisional control (...)”.



Department of Psychology The University of Western Ontario

Use of Human Subjects - Ethics Approval Notice

Review Number	07 03 01	Approval Date	07 03 01
Principal Investigator	Jim Neufeld	End Date	07 11 30
Protocol Title	Coping with stress through decisional control: Investigating formal and quasi-formal models		
Sponsor	n/a		

This is to notify you that The University of Western Ontario Department of Psychology Research Ethics Board (PREB) has granted expedited ethics approval to the above named research study on the date noted above.

The PREB is a sub-REB of The University of Western Ontario’s Research Ethics Board for Non-Medical Research Involving Human Subjects (NMREB) which is organized and operates according to the Tri-Council Policy Statement and the applicable laws and regulations of Ontario. (See Office of Research Ethics web site: <http://www.uwo.ca/research/ethics/>)

This approval shall remain valid until end date noted above assuming timely and acceptable responses to the University’s periodic requests for surveillance and monitoring information.

During the course of the research, no deviations from, or changes to, the protocol or consent form may be initiated without prior written approval from the PREB except when necessary to eliminate immediate hazards to the subject or when the change(s) involve only logistical or administrative aspects of the study (e.g. change of research assistant, telephone number etc). Subjects must receive a copy of the information/consent documentation.

Investigators must promptly also report to the PREB:

- a) changes increasing the risk to the participant(s) and/or affecting significantly the conduct of the study;
- b) all adverse and unexpected experiences or events that are both serious and unexpected;
- c) new information that may adversely affect the safety of the subjects or the conduct of the study.

If these changes/adverse events require a change to the information/consent documentation, and/or recruitment advertisement, the newly revised information/consent documentation, and/or advertisement, must be submitted to the PREB for approval.

Members of the PREB who are named as investigators in research studies, or declare a conflict of interest, do not participate in discussion related to, nor vote on, such studies when they are presented to the PREB.

Clive Seligman Ph.D.

Chair, Psychology Expedited Research Ethics Board (PREB)

The other members of the 2006-2007 PREB are: Mike Atkinson, Bertram Gawronski, Rick Goffin, Jim Olson, and Matthew Maxwell-Smith

CC: UWO Office of Research Ethics

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5 Decisional Control Modeling for Choice Type, Structure, and Number Predicts Patterns of Stress Response

5.1 Introduction to the Fifth Component Document

The fifth component document, a second empirical study, is the culmination of many stages of previous work. This study is extensively informed by model structure (Neufeld, 1982; Shanahan, Nguyen, & Neufeld, in preparation, see Chapter 2; Shanahan & Neufeld, in preparation, see Chapter 3), simulation findings (Shanahan, 2007; Shanahan & Neufeld, 2010a, 2010b), and previous study designs (Morrison, Neufeld, & Lefebvre, 1988; Kukde & Neufeld, 1994; Benn, 1995, 2001; Shanahan, Pawluk, Hong & Neufeld, in preparation, see Chapter 4 in this dissertation). Based on these beginnings, this study examined whether the expected *theoretical relations between decisional-control model properties* would hold as predicted under empirical testing. Briefly: yes, they did.

As an empirical validation of *relations between theoretical quantities*, this investigation is an ambitious and now-vindicated implementation of a constellation of expectancies generated by the decisional-control model. For a scientific statement to be respected as intelligently describing observed phenomena, it must necessarily be exposed in some kind of objective evaluation to the *possibility of being wrong* (cf. ‘falsifiability’ in Popper, 1935/2002). A delightful chain of interdependence is legitimized when mathematical intricacy provides falsifiability via detailed expectancy prescriptions, falsifiability of experimental predictions provides meaningful interpretation for anticipated results, and obtained findings are consistent, at least to some extent, with experimental predictions and theoretical expectancies. Obtained findings then communicate validity to the design, support to the hypothesis, and realism to theoretical constructions. As a touchstone for the meaning of findings and validity of experimental method, we call the pursuit of a strong presupposed theoretical result with novel and highly speculative experimental design an ‘invisible-goaled standard’.

5.2 “Decisional Control Modeling for Choice Type, Structure, and Number”

The manuscript-form of this experimental study follows, below.

Decisional Control Modeling for Choice Type, Structure, and Number

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The University of Western Ontario
Research Support: Social Science and Humanities Research Council of Canada
2015

Abstract

Previous decisional control research theoretically predicts three potentially observable phenomena. First, simulation results and empirical study of decision-making situations suggest a reliable strong negative correlation between assessed likelihood of obtaining the lowest threat $Pr(t_1)$ ('best option') and calculated reduction in overall threat $E(t)$ proper to a decision-making structure. More specifically, the correlation between $Pr(t_1)$ and $E(t)$ is also expected to predictably attenuate with larger numbers of items to evaluate. Second, simulation work predicts a statistically explicable impairment in threat-reduction effectiveness when 'uncertainty' (*unknown* external assignment of selection at a hierarchy level: a 'node') is subordinate to 'choice' (information and executive power at that node) in a decision hierarchy. This unique obstructiveness of choice architecture 'CU' (choice at the higher node, uncertainty at the lower node) to threat-reduction contrasts significantly with both of its nearest structural counterparts, 'UC' ('uncertainty' node over a 'choice' node) and 'CN' ('choice' node over 'no-choice' node; no-choice 'N' is *known* external assignment of selection). Contrasting CU with UC and with CN experimentally is a novel undertaking. Third, previous research suggests a 'two-source model of stress', arising from scenario-specific, nonconscious but behaviorally observable bilateral evaluation by the decision-maker of information processing demands and degree of exposure to a negative outcome. This pattern has been observed previously with minimum heart rate, duration of decision-making, and subjective stress as dependent measures. Theoretical synthesis successful in previous research is used to analyse results as an independent test of the proposed theoretical mechanisms.

Keywords: stress and coping, decisional control, threat reduction, two-source model.

Investigations into decisional control, the ability to influence one's stress status via decision-making, have yielded certain findings consistently. These include findings that: (a) choice does decrease objective threat in decision-making situations, and participants perceive this, (b) there are psychophysiological indications of participant perception of threat, and (c) participants' behavior is sensitive to the architecture and features of decisions arranged in a different hierarchical patterns. The present study is anchored in this decisional control research (listed following), particularly research done under the governing paradigm of a formal model of decisional control developed by Neufeld and colleagues (Neufeld, 1982; see also Kukde & Neufeld, 1994; Morrison, Neufeld, & Lefebvre, 1988, Shanahan & Neufeld, 2010a, 2010b).

Findings come under three major headings: modeling of expected cognitive operations, detection of decisional control through its impact on behavioral, subjective, psychophysiological variables, and interaction with a backdrop of published psychometric instruments representing constructs with a known relation to decisional control. Recent analyses suggest that theoretical expectation of 'return on investment' for a decision may influence participant responses in terms of duration of decision-making, subjective experience of stress and heart rate deceleration within an experimental trial.

This study examines the validity of the model of decisional control put forward by Neufeld and colleagues (e.g. Neufeld, 1982; Shanahan & Neufeld, 2010a). Refinements include the use of a wider and more complex array of experimental levels than any array previously researched empirically, and the coordination of psychophysiological, reaction time and subjective stress data on a per-trial basis. Together with certain psychometric instruments new to the decisional control paradigm, this study creates, deepens, and

improves understanding of the probabilistic expectancies of modeled hierarchical decision-making as observed in participant behavior.

Decisional Control Model Concepts and Quantities

Decisional control as a form of coping with stress has been delineated in a mathematical modeling approach to threat reduction (e.g. Morrison, Neufeld, & Lefebvre, 1988). The model is a formally-defined platform for quantifying concepts within decisional control, such as information-processing load, and threat reduction. Specific constructs become tractable for simulation work, in turn generating precise predictions open to falsification. The hypotheses informed by these predictions will be reviewed, as well as the experimental approach to them and the instruments used to measure psychophysiological, psychometric, and reaction time data.

Behavioral control, cognitive control, and decisional control.

Appraisal of stressful situations has been proposed as fundamental to understanding the human stress response (Lazarus & Folkman, 1984). Central to appraisal is the role of cognitive evaluation of possible *outcomes* and of possible *responses* that can lead to those outcomes. In essence, this is decisional control. Decisional control was originally defined as one of three types of control that can be used in responding to stress: behavioral control, cognitive control, and decisional control (Averill, 1973).

The first and simplest form of control, *behavioral control*, describes the reduction of stress by a participant's direct action on the participant's environment. Turning down the volume on a sound system if it is painfully loud is an example of exercising behavioral

control. A second, more abstract form of control is *cognitive control*. This describes the reduction of stress by altering one's interpretation of a noxious stimulus. Learning that a large number of people in a university dormitory can tolerate loud music without much consternation may help a new student reinterpret such a stressful situation so as to experience less stress, especially from ego-based personal irritation. Gaining information and using it in this way exemplifies cognitive control available to a person under stress.

The third and most relevant form of control for our study is *decisional control*.

Decisional control combines aspects of behavioral control and cognitive control, and it adds the supplementary dimension of their interaction whereby a course of action (or a decision, similar to behavioral control) is selected through information-processing (similar to cognitive control). Decisional control has the unique distinction of informing behavioral control with considered options, and of bringing perspective to cognitive control in terms of a principled estimation of relative impact of outcomes. Ideally, a measure of increased realism is introduced to the stressful situation from both avenues. To extend the examples given, a student might evaluate the chances of success on an upcoming exam offered by either: (a) using earplugs and studying at the dormitory, or (b) studying at a library site with extended hours.

Choice type, structure, and number.

Decisional control is applied in the context of *decision hierarchies*, where a set of decisions govern underlying, 'nested' sets of decisions. In this study, a single level of nesting (also called 'first-order scenarios') only is assessed experimentally. These consist of a group of 'bins' within which groups of 'elements' are nested. Considerable

theoretical work has been done on two-levels of nesting ('second-order'), but this degree of nesting is more complex and was not included in this experiment. Each level of decision-making can be called a 'node', and at each node a *specific type of choice condition* can be available. These are: free choice ("C") among options at a given hierarchy node; no-choice ("N"), whereby selection is done externally, but the selected option is communicated to the decision-maker (DM), and uncertainty ("U"), where the selection is done externally and is not communicated to the DM. When describing the nine possible arrangements of three choice conditions (C, N, U) at the 'bin-level' and the 'element-level', the convention is to list the bin-level first as super-ordinate in the hierarchy and the element-level second as subordinate. Thus, a scenario with bin-wise choice and element-wise no-choice is structurally described as 'CN'. Again, bin-wise uncertainty and element-wise choice is labeled 'UC'. This structure is important for the mathematical-combinatoric logic governing the probability of obtaining a better or worse threat value in a given situation. Finally, the decisional control model uses algebraic quantities for numbers of bins and elements: p "bins" each nesting q "elements" (by comparison, second-order structures use P "bin-sets", each nesting p "bins", each in turn nesting q "elements"). These are important operationalizations within the model, allowing for the formulation of structurally-based indices of number of options, cognitive judgments, and probabilistic expectancies of obtaining particular threat values. This process determines probability of occurrence of an undesirable outcome (the "threat").

Decisional control, information-processing demand, and threat reduction.

These phenomena are described more extensively, together with simulation-based explorations, by Shanahan and Neufeld (2010a) in a simulation-based study that

expanded previous findings and theory (Kukde & Neufeld, 1994; Morrison, Neufeld, and Lefebvre, 1988). Developed in the initial formulation (Morrison et al., 1988; Neufeld, 1982), the model relies on three major constructs: decisional control, information-processing demand, and threat reduction. Each of these is indexed to specific quantifications within the model.

The first construct is decisional control, the degree to which individual decision-making affects the likelihood of facing an undesirable event. The quantity used to represent the construct of decisional control is *response set size (RSS)*. This quantity, *RSS*, is the number of potential selections available to the decision-maker. In a situation with fully external assignment (no freedom of choice), *RSS* is 1; there is only one ‘option’. The logic for indexing this quantity to decisional control is that number of potential selections (and, more pointedly, *exclusions*) increases the degree of influence available for reducing stress through decision-making.

The second construct is information-processing demand, a construct related to cognitive load or degree of intellectual effort required to evaluate available options. The quantity used to represent the construct of information-processing demand is *outcome set size (OSS)*. This quantity, *OSS*, is the number of potential encounters with distinct threat levels that the DM may have to face. The quantity *OSS* differs from *RSS* in that the model assumes the threat level involved in relevant situations is enough to induce the DM to evaluate those possibilities that still may be assigned but over which the DM has no control (Condition U; discussed at greater length in Kukde & Neufeld, 1994; Morrison, Neufeld, & Lefebvre, 1988; also addressed in Monat, Averill, & Lazarus, 1972, and Gaines, Smith, & Skolnik, 1977, as cited in Neufeld, 1982). For example, if a situation

has a CU configuration (super-ordinate node has Choice and subordinate node has Uncertainty), with a $p = 2$ and $q = 2$, then *response set size* $RSS = 2$ (choice between 2 bins at the 'C' node), and *outcome set size* $OSS = 4$ (4 potential encounters, or, threat level values: 2 elements in each of 2 bins).

The third construct of particular interest is threat reduction. The degree of reduction in threat facing the DM can be calculated by comparing the *expected threat* $E(t)$ between situations with different parameters. Expected threat is calculated with mathematical-combinatoric formulations proper to each particular arrangement of C, U, and N in a decision scenario. These are available in previously published material (Shanahan, 2007; Shanahan and Neufeld, 2010a, 2010b). The expected threat calculation yields a probability that the adverse event a DM wishes to avoid will still occur (bounded by 0, impossibility of occurrence, and 1, certainty of occurrence). With this quantity, the objective degree of potential *threat reduction* can be ascertained by comparing the *expected threat* calculation for different p and q parameter values (or P , p , and q parameter values), for different threat levels t_i , and for different scenario architectures (e.g., CC vs. CN).

Relations between model quantities.

Specific relations between the above-described quantities have been found and explored (Morrison et al, 1988; Shanahan and Neufeld, 2010a, 2010b). The use of response set size (number of choices available) as a reliable predictor of the expected threat the subject will have to face (also known as *mathematical expectation of threat*) was validated across a comprehensive range of scenario parameters, in both two-level and three-level

hierarchies. Additionally, explanations for individual differences in decisional-control preference presented by Morrison and colleagues (1988) have been confirmed and further developed by Shanahan and Neufeld (2010a). In particular, a negative low moderate correlation between the model's measure for information-processing load (*outcome set size*) and expected threat after optimal decision making supports the observed divergence in decisional-control profiles (Kukde and Neufeld, 1994; Morrison et al., 1988). To put it succinctly, there is no "clear winner" among strategies related to total number of possible outcomes. Specifically, exhaustive evaluation of prospects confers some benefit, but exhaustive evaluation may prove more "exhausting" to some individuals than to others, in terms of expenditure of cognitive effort (see Townsend & Ashby, 1978, as cited in Neufeld, 1990; see also, Neufeld, Townsend, & Jetté, 2007). At the level of the analysis conducted, there is no best strategy apparent for a sizeable random sample of individuals.

Hypothesis I: Chance at 'Best Option' Predicts Lower Expected Threat, Predictably

New sets of predictions that remain to be tested are twofold in type. The first type of prediction concerns a more refined mapping of the strong negative correlation between the amount of decisional control available and expected threat. The second type concerns the uncertainty condition in relation to the choice condition, especially by contrast with the no-choice condition. For the first set of predictions, the quantity metric used for decisional control is the objective calculation of the probability of access to the least threatening option, assuming a maximizing decision strategy (DM makes selections with the intent of obtaining the lowest threat value, the 'best option'). The extensive simulations in Shanahan and Neufeld (2010a, 2010b) create a vast, parameter-defined expanse of correlation values to be examined and considered. A specific pair of

parameter values p, q (where p is number of bins within each of which q elements are nested) will have a specific predicted correlation between amount of available decisional control (tied directly to number of available responses), and mathematical expectation of threat. This correlation holds within this model for a given pair (p, q) of set size values, independent of specific threat ranges or values.⁴

The first general hypothesis to be explored will be the prediction of the correlation of decisional control to threat reduction, as discussed above. Here again, the end-points and representative specific mid-points will be selected and tested in a similar way. These points are mapped not by scenario structure (CC, NC, etc.) but rather by nodal set size parameters (p, q) pairs). Table 1 below illustrates the selected test points, chosen for regular decrements of about 10% in predicted percentage of variance (*r-squared*) accounted for by the correlation between $Pr(t_1)$ and $E(t)$, or, the probability of access to the least threatening option and the mathematical expectation of threat. The calculation of these values was done individually, but the computational aids (decisional control spreadsheets) that are available online and described in Chapter 3 allow for rapid calculation of the value sets for any p and q values that form a pq product of 100 or less, when values for p and for q are 2 or higher.

⁴ The use of correlation measures between decisional control and expected threat result in the exemption of this relation from scaling effects of specific threat levels. Thus, all necessary information to describe degree of association is contained in the parameter values $(P), p, q$ (see online supplement at <http://publish.uwo.ca/~mshanah>). This assumes values are averaged across all combinations of C, U, and N for a given hierarchy size of interest.

Table 1

Proposed Pairs for Empirical Exploration of $Pr(t_1)$ -- $E(t)$ Correlation

First-Order Pair	$Pr(t_1) \propto E(t)$ <i>r</i> value	$R^2 \times 100\%$, or % variance accounted for
2,2	-.9527	90.76%
7,2	-.8951	80.12%
4,3	-.8360	69.89%
4,5	-.7737	59.86%
5,7	-.7080	50.13%
9,7	-.6321	39.96%

In Table 1, above, note that both the magnitude and the trend of correlation and percentage of variance accounted for in $E(t)$ by $Pr(t_1)$ is being predicted. This is a particularly 'bold' conjecture (cf., Popper, 1935/2002), in that it is open to being wrong both in the expected strength of correlation and the expected pattern of attenuation. Even partial confirmation of these expected values and predicted trend should be considered an important success for our research and a vindication of decisional control model utility.

Hypothesis II: 'Choice into Uncertainty', CU, as Comparatively Highly Stressful

The second type of predictions concerns the effect of uncertainty as detrimental to the successful exercise of decisional control. Uncertainty is defined in this model as the external assignment of a selection at a given node in the decision hierarchy, where the knowledge of this external selection is not available to the decision-maker when decisional control is being exercised at other nodes within the same decisional scenario. In particular, making choices "into uncertainty", whereby choice by the decision-maker at

a higher node is followed by external unknown assignment at a dependent (subordinate) node is predicted to particularly hamper most of the benefit from available choice.

As can be observed in Table 2 below, there are different scenario architectures that comparatively facilitate or impair threat-reduction (a lower value for $E(t)$). Of particular scientific interest are those scenarios with mixed choice conditions (different decision-making power at different hierarchy nodes). Comparing these structurally-embedded differences yields an informative profile of threat-reduction potential.

Table 2

List of first-order scenario architectures by increasing mean $E(t)$

First-order scenarios equivalent in mean $E(t)$	Mean $E(t)$, exhaustive p, q list *	Maximum $E(t)$ for single set, p, q values	p, q values for maximum $E(t)$	Minimum $E(t)$ for single set, p, q values	p, q values for minimum $E(t)$
CC	.1000	.1000	all values	.1000	all values
CN,UC,NC	.2242	.3937	2,50;50,2;50,2	.1088	50,2;2,50;2,50
CU	.4625	.5405	2,50	.3247	21,2
UU,UN,NU,NN	.5450	.5450	all values	.5450	all values

* For $t_1 = .1$, $\max t_i = .99$, $\Delta t_i = (\max t_i - t_1) / (pq-1)$, exhaustive p, q values (all 283 possible pairs within specified constraints). Table adapted from Shanahan (2007).

In Table 2, the mean level of expected threat for NC/UC scenarios is .2242, whereas the comparable mean level of expected threat for a CU scenario is .4625 (absolute boundaries are 0.0000 and 1.0000). This can be interpreted as a 22% chance of the undesirable outcome in NC or UC decisional control hierarchies, but a 46% chance of the undesired outcome under CU hierarchies, calculated across a balanced array of different parameter values (p, q). Note that the most important leverage in decisional control occurs with

increase in the set size (p or q value, as the case may be) at the node where choice 'C' is operative.

With parameter values balanced across a large range however, as reported in Table 2, the fundamental structural disadvantage of a 'CU' pattern emerges. The obstruction to decisional control associated with a lack of information under subordinate uncertainty can be evaluated by comparing the CU condition and the UU, UN, NU, and NN family of homogenous threat expectancy conditions. The eventual threat value (and outcome) under CU becomes much more subject to a random distribution of occurrences, as is fully the case in the four structures with no 'choice' available at all (UU, UN, NU, NN). Specifically in Table 2, it can be observed that under a CU structure generally, the probability of the undesirable outcome is 0.4625 (about 46%), thanks to some decisional control from selection at the bin-level 'C' node. This is, however, only a slight improvement over an expectancy of 0.5450 (about 55%) for outcomes determined by random distribution of untoward occurrences (i.e., 0.5450 is the exact mid-point between the lowest threat value of 0.100 and 0.990).

In terms of $E(t)$ comparisons, note that the 'CC' scenario will always return a value equal to t_1 because this is the best option and full choice to obtain it is granted at both the bin and element level. In generating Table 2, t_1 was set to 0.1, as per the table caption.

Similarly at the other 'end-point', scenarios with no nodes offering choice 'C' at all (NN, NU, UN, UU) operate by purely random allotment of threat values. As such, their $E(t)$ value is the exact mean value between t_1 and t_{pq} , the minimum and maximum threat values in an evenly dispersed threat list. These first and last threat values were set to 0.1 and 0.99, respectively, and the average of these two values is the depicted $E(t)$ value,

0.5450. As such, the more ‘interesting’ values, subject to non-trivial variation are the CN, NC/UC and CU values. Note that in a fully balanced array of p and q values, CN and NC/UC have the same expectation. Note, however, that a greater decrease in $E(t)$ will occur in the decision scenario with the larger set size value at the ‘C’ node. The related scenarios NC/UC are calculated identically, and so can be grouped together for $E(t)$ in all circumstances. Their bin-choice analog, CN, however, will benefit from a higher p value for number of bins, whereas NC/UC will lower $E(t)$ more effectively with a relatively higher q value for number of elements.

Test of Theoretical Formulation

One more assessment will be done in this study. Bearing on a theoretical mechanism used to explain findings in a related study (see Chapter 4), a specific procedure for generating expectancies in decision-making preference among participants will be used. The expectation of decision-maker preference is based on a two-source conceptualization for stress in decision-making: the stress of the threat being faced, and the anxiety regarding the demands of information processing to reduce this threat. This procedure emerges from the most recent empirical study using the decisional control model (Chapter 4), and is also described in the Results section, further below.

Dependent Measures

The measures of stress used will be Likert-type ratings of subjective stress (as per methodology in Hong, Shanahan, Pawluk, and Neufeld, 2008). The other indicators of stress will be duration of decision-making, with more time indexing greater stress, and a psychophysiological measure of cardiac reactivity, heart rate deceleration. Heart rate

deceleration, also known as minimum heart rate per-trial (HRDEC) has been found in previous research (see Chapter 4 in this dissertation document) to vary meaningfully with expected model-driven variations in situational threat. This value is found by subtracting the lowest sampled heart rate during a rest period between trials from the lowest sampled heart rate associated with task completion during trials. In addressing evidence a strong negative correlation between the reactivity score of HRDEC and Decision-Making Time (RT1) and Single-Trial Rating of Subjective Stress (STRSS), it is possible to invert the *sign* of the reactivity scores, if it is simpler to align all three measures. This is most easily accomplished by subtracting scores recorded during task completion *from* baseline scores. Something like this procedure will be conducted later in this study to allow simplification of the inspection of visual patterns of results without the need to invert HRDEC values.

Study Design, Hypothesis Statements, and Provisional Expectations

The goal of the current research is to validate, with empirical findings, predictions derived from simulations based on the decisional control model of stress and coping (Shanahan & Neufeld, 2010a, 2010b). Comprehensiveness beyond existing levels of empirical support (Kukde & Neufeld, 1994; Morrison et al., 1988) is one of the main aims of the present study in particular. To this end, scenarios instantiating the extreme anchor points in which decisional control is theorized to act will likely either be most or least effective. Selected points between these predicted extremes (in an arrangement of increasing predicted decisional control) will be tested for validation. Anchor points in the case of uncertainty scenarios are defined by scenario architecture.

In order to test both Hypotheses I and II, a 9 x 6 experimental grid of cell conditions was developed. The nine possible choice structures that emerge by permuting the three choice types in the two levels of first-order hierarchies are all represented (CC, CN, CU, NC, NN, NU, UC, UN, and UU). The six pairs of p and q parameter values depicted in Table 1 are the six independent variable ‘levels’ that vary ‘choice number’ as a key research question in this study. At each of these levels, standard decisional control methodology with situational vignette, decisional control hierarchy presentation, and response registration is used while recording duration of decision-making, psychophysiological readings, and participant rating of per-trial subjective stress.

The specific hypotheses to be tested are:

1. The percentage of variance accounted for in $E(t)$ by $Pr(t_1)$ will be similar to the pattern observed in Table 1, using decision-making time RT1, single-trial rating of subjective stress STRSS, and heart rate deceleration reactivity HRDEC as empirical proxies for $E(t)$, reflective of participant stress.
2. The uncertainty effect will be observable in comparisons between choice structures such that for each of RT1, STRSS, and HRDEC, higher stress will be registered according to choice structure as follows:
 - a. $\text{Stress}(\text{CU}) > \text{Stress}(\text{UC})$
 - b. $\text{Stress}(\text{CN}) < \text{Stress}(\text{CU})$
 - c. $\text{Stress}(\text{CC}) < \text{Stress}(\text{NN})$
 - d. $\text{Stress}(\text{NN}) = \text{Stress}(\text{UU})$

These four comparisons are designed to assess model assumptions either directly (a., b.) and indirectly (c., d.) regarding the uncertainty choice condition.

3. Theoretical formulations for 'decision value' can be used to predict and describe stress patterns in the current experiment. Where the decisional control model applies, the two-source model of stress for 'decision value' will also apply. Two pairs of parameter set values (2, 2) and (7, 2), and (4, 3), and (4, 5) will be used in an attempt to replicate findings in Chapter 4.

Methods

Participants

Sample and recruitment.

Participants were recruited from a mainly undergraduate sample in the summer of 2011. We recruited participants via a summer contact list and a poster. Requirements were: right-handedness, no known hearing problems, and good English reading comprehension. Approximately 1.5 to 2.0 hours participation was advertised, and a sum of 15\$ was to be given as remuneration. Interested readers were to contact the research team by email (a dedicated Gmail account), and were then referred to a online scheduling website (SignUpGenius) for further instructions and to sign-up for established appointment slots.

Sample characteristics.

Overall, 77 participants completed our study (35 males, 42 females). After exclusions for age (35 or older) and poor data quality, a total sample of 69 participants (34 males, 35 females) remained, with one male not indicating a value for Age. This final sample had a mean age of 21.9 years (range, 17 to 31) and was not kurtotic or skewed.

Apparatus

The various equipment used consisted of three separate hardware and software platforms, one each for psychometric, cognitive, and psychophysiological data collection modes.

Psychometric and questionnaire research platforms.

Psychometric data collection was done via a programmed set of questionnaire screens in SurveyGizmo, an online questionnaire website. These questionnaires were completed in the data collection area of the research laboratory. One psychometric measure was collected prior to the experiment, the Wonderlic Personnel Test - QuickTest (WPT-Q; a brief measure of cognitive ability). This 8-minute timed test was administered via the participants' own computer platform ahead of data collection, on a site hosted by the Wonderlic Corporation. Once recruited to our study, the participant was advised to expect notification by email for login to the Wonderlic online site and complete the WPT-Q as instructed.

Cognitive research platform for stimulus presentation.

Cognitive data collection was accomplished via an E-Prime 2.0 software platform. Sets of stimuli involving complex presentations were programmed and presented so as to engender cognitive processing and decision-making within rules consistent with the decisional control paradigm. It must be noted that programming a decisional-control paradigm into E-Prime 2.0 was highly intensive, and on several occasions, initial programming exceeded E-Prime parameter limits for number of lines of code. The efforts of the second author in this regard are specially acknowledged.

Psychophysiological apparatus.

The psychophysiological data collection equipment used was manufactured by Biopac. The particular unit, used previously in this type of research, is the MP-150 Data Acquisition System, with addition of the STP-100 module for this study. This combination of equipment allows for monitoring of heart rate acceleration and deceleration, which have been respectively associated with covert processing and with stimulus intake. Monitoring involves placing electrodes bilaterally on 5 sites: at the top and base of the neck, chest, at the top and bottom of the lower torso – altogether, 10 electrode placements. Specific cardiac impedance channels are registered and transformed to produce values for Cardiac Output (CO), Total Peripheral Resistance (TPR), and Heart Rate (HR; including heart rate deceleration, HRDEC). The software package AcqKnowledge 4.1 was used as the standard accompaniment to the Biopac equipment.

Desktop computer speakers were used to generate white noise for informed consent and feedback accumulated conditionally according to task performance. A video camera was used to collect facial expressions in view of possible future analysis of facial reactions.

Measures

Published measures of psychometric properties for cognitive ability, intolerance of uncertainty, internal locus of control, coping style, and decision-making style were administered via computer terminal to obtain personality characteristics of participants relevant to decisional control. Additionally, a control measure for participant stress was

also administered at three time points: before the experimental session, after training but before experimental trials, and at the end of the experimental session.

Wonderlic Personnel Test.

The short form of the Wonderlic Personnel Test, the “Wonderlic QuickTest” (WPT-Q, 30 items, 8 minutes timed) is a brief online version of a well-validated test of cognitive ability. The Wonderlic QuickTest is supported as predictive of the Wonderlic Personnel Test and a useful abbreviation of the paper-and-pencil measure. A correlation of $r = 0.77$ is reported between the WPT-Q and WPT (Wonderlic, 2004; as cited in Wright & Meade, 2011). The online site for the WPT-Q is hosted by the Wonderlic Corporation, and is represented to researchers by this major psychometric measurement company as secure. Cognitive ability is an important control variable for our decision-making research.

The original Wonderlic Personnel Test (WPT; Wonderlic & Hovland, 1939) was a 12 minute paper-and-pencil test of cognitive ability. The WPT is a standard industrial psychology assessment tool and provides a good prediction of general intelligence, as supported by comparison with other standard measures such as the Wechsler Adult Intelligence Scales (e.g., .93 correlation with WAIS FSIQ in Dodrill, 1981; .92 correlation with WAIS-R in Hawkins, Faraone, Pepple, Seidman, Tsuang, 1990; all the preceding, as cited in Restrepo, 2008). Construct validity emerged in our sample with a mean of 25.2 (see Results section). Average intelligence is theoretically anchored at 25 on the WPT, the equivalent of 100 on a standard IQ test.

Intolerance of Uncertainty Scale.

The Intolerance of Uncertainty scale (IUS, 27 items; Freeston, Rheaume, Letarte, Dugas, & Ladouceur, 1994) was developed to assess emotional, cognitive, and behavioral reactions to contexts of uncertainty in life situations, implications of life situations, and the future. Although several areas of possible uncertainty are included, the IUS measure is used as a single summary score. Supporting such use is a reported internal consistency of $\alpha = 0.91$. Items include, for example: “I should be able to organize everything in advance”, “When I am uncertain, I can’t go forward”, and “When it is time to act, uncertainty paralyzes me”. These are rated on a Likert-type scale from 1 “Not at all representative [of me]” to 5 “Completely representative [of me]”. Convergent validity is reported (Freeston, et al., 1994) with correlations on related measures of 0.63 with the Penn State Worry Questionnaire (PSWQ), 0.57 with the Beck Anxiety Inventory (BAI), and 0.52 with the Beck Depression Inventory (BDI). Reliability in our sample, calculated across 62 participants with answers for all 27 items, was associated with an internal consistency of $\alpha = 0.92$.

Internal Control Index.

The Internal Control Index (ICI, 28 items; Duttweiler, 1984) was developed as a refinement of the locus of control put forward by Rotter (1954). Locus of control is an extensively researched concept, and Patricia Duttweiler argues for a unipolar approach to it. She proposes that an *internal sense of control* that is more or less present as a personality trait, rather than a bi-polar concept of an internal and an external locus of control. As such, internal control is the degree to which an individual perceives personal

responsibility and effective influence on his or her life surroundings and outcomes. Internal reliability is reported as $\alpha = 0.84$ and 0.85 for two large samples. Evidence of convergent validity is reported as a negative correlation of $r = -0.385$ with Mirels' Factor I of Rotter's I-E Scale (a factor related to attribution of personal outcomes to luck or chance – 'external' controlling forces). Items from the Internal Control Index include, for example: "If I want something I work hard to get it," and "I let other peoples' demands keep me from doing things I want to do." (reverse scored). Items are rated by use of an A through E endorsement of each item, where (A) is anchored to "RARELY (less than 10% of the time)", (B) is "OCCASIONALLY (About 30% of the time)", (C) is "SOMETIMES (About half the time)", (D) is "FREQUENTLY (About 70% of the time)" and (E) is "USUALLY (More than 90% of the time)". These endorsement levels are scored with a value of 1 to 5 from A to E, or 5 to 1 for reverse scored items. A high score in the Internal Control Index is interpreted as a strong sense of personal influence over one's own circumstances and outcomes. Reliability in our sample, calculated across 63 participants with answers for all 28 items, was associated with an internal consistency of $\alpha = 0.83$.

Ways of Coping scales.

The Revised Ways of Coping Inventory (WC, 66 items; Folkman and Lazarus, 1985) is an adaptation of an instrument first used by Folkman and Lazarus in earlier research (1980). This inventory is meant as an assessment of an individual's coping process. As such, it is not originally intended to be used to capture coping style as a trait. Nonetheless, endorsement of use of coping strategies on eight separate scales gives an indication of a participants' stress process and strategies with regard to a specific,

significantly stressful event encountered within the previous month. Based on a student-specific sample, the eight scales (with reliability coefficient value) are: Problem-focused Coping (.88), Wishful Thinking (.86), Detachment (.74), Seeking Social Support (.82), Focusing on the Positive (.70), Self-blame (.76), Tension Reduction (.59), and Keep to Self (.65). Rating is done on a 0 to 3 scale, with 0 described as “Not Used”, 1 as “Used Somewhat”, 2 as “Used Quite a Bit”, and 3 as “Used a great deal”, with regard to the coping strategy item. Item statements include, for example: “I know what has to be done, so I am doubling my efforts to make things work.” (Problem-focused Coping), “I daydream or imagine a better time or place than the one I am in.” (Wishful Thinking), and “Realize I brought the problem on myself.” (Self-blame).

We calculated internal consistency statistics in the present sample for each of the WC scales: Problem-focused Coping ($\alpha = .71$, 11 items, 65 cases), Wishful Thinking ($\alpha = .81$, 5 items, 68 cases), Detachment ($\alpha = .60$, 6 items, 68 cases), Seeking Social Support ($\alpha = .70$, 7 items, 66 cases), Focusing on the Positive ($\alpha = .71$, 4 items, 65 cases), Self-blame ($\alpha = .75$, 3 items, 69 cases), Tension Reduction ($\alpha = .05$, 3 items, 68 cases), and Keep to Self ($\alpha = .51$, 3 items, 67 cases). Note that Tension Reduction here presents essentially no reliability ($\alpha = .05$), such that the items “Got away from it for a while; tried to rest or take a vacation”, “Try to make myself feel better by eating, drinking, smoking, using drugs or medication, etc.,” and “I jog or exercise” appear to covary not at all. This is the scale with the lowest reliability reported by Folkman and Lazarus ($\alpha = .59$; 1985). The subscale “Tension Reduction” should not be considered a reliable subscale in this sample; as such, it will be kept in analyses for completeness in using the Ways of Coping Scales, but it will not be interpreted. For its part “Keep to Self” shows some degree of cohesion, but a

lower reliability coefficient than is usually acceptable ($\alpha = .51$) for personality research purposes.

General Decision-Making Style questionnaire.

The General Decision-Making Style questionnaire (GDMS, 25 items; Scott & Bruce, 1995) categorizes five patterns of decision-making: Rational, Intuitive, Dependent, Avoidant, and Spontaneous. Internal consistency is reported for each of the five styles across four large samples as ranging from .68 to .94, an acceptable range for personality research purposes. Sample items include, for example: “My decision making requires careful thought” (Rational), “When making decisions, I rely upon my instincts.” (Intuitive), “I rarely make decisions without consulting other people.” (Dependent), “I postpone decision making whenever possible.” (Avoidant), and “I generally make snap decisions,” (Spontaneous). Items are rated on a five-point Likert-type scale from *strongly disagree* to *strongly agree*. Content validity is reported by Scott and Bruce (1995) as deriving from an extensive search of theoretical and empirical research literature.

Independent researchers reviewed items for face and logical content validity. Concurrent validity is supported by differential proportions of decision-making style endorsements, in expected directions, between samples of military officers, MBA students, and undergraduate. Construct validity is supported by a higher endorsement of rational decision-making style and lower endorsement of avoidant decision-making style among individuals with a higher internal control orientation (cf. Duttweiler, 1984, ICI mentioned above). Interestingly, individuals rated as internally controlled and those rated as externally controlled endorsed similar levels of intuitive decision-making.

We calculated the internal consistency values for the five styles: Rational ($\alpha = .68$, 4 items, 68 cases), Intuitive ($\alpha = .82$, 5 items, 68 cases), Dependent ($\alpha = .82$, 5 items, 66 cases), Avoidant ($\alpha = .92$, 5 items, 68 cases), and Spontaneous ($\alpha = .85$, 5 items, 67 cases). These values correspond closely to the range of reliability coefficients reported by Scott and Bruce across the five styles (from $\alpha = .68$ to $\alpha = .94$; 1995).

Stress Adjectives Checklist.

The Stress Adjectives Checklist (SACL, 18 items; Cruickshank, 1984; King, Burrows, & Stanley, 1983) is an adaptation of MacKay and colleagues' Mood Adjective Checklist (1978). Cruickshank (1984) shortened the list of stress adjectives to remove low frequency words (often unfamiliar to the participant) and to equalize the number of positive and negative stress words. Cruickshank reported internal consistency alpha of 0.94. Research by King, Burrows, and Stanley (1983) further refined and validated the use of the Stress Adjective Checklist for discriminating between groups. The Stress Adjective Checklist is used as a control measure in our study, assessing for individual differences in stress levels at the beginning of the experimental session, the beginning of experimental trials (after the training required), and at the end of the experiment. Participants endorse 18 stress-related words with ratings of two 'plus signs' ("++": 'definitely yes') indicating strong endorsement, one plus-sign indicating endorsement ("+": 'slightly yes'), a question mark indicating no endorsement ("?": 'not sure or don't understand'), or a negative sign ("--": 'definitely not') indicating lack of clear presence of the stress-related concept. Scoring can be done with four points given to 'definitely yes', three for 'slightly yes', two for 'not sure or don't understand', and one point for 'definitely not'. A higher value is indicative of higher stress.

In our sample, an alternate scoring method was used (as per Cruickshank, 1984). The reasoning for this alternate method was that presence and absence of the stress-related word is more clearly registered by 1 or 0 values. By comparison, using four positive natural numbers, 1, 2, 3, 4, to reflect absence, uncertainty, slight and strong endorsement (“definitely not”, “not sure / don’t understand”, “slightly yes”, “definitely yes”) seems a less numerically authentic mapping. Instead, positive item endorsement (slight or strong) was coded a ‘0’, absence, a ‘1’; conversely, negative item endorsement (slight or strong) was given a ‘1’, absence a ‘0’. This yields a SACL with higher scores indicating higher stress (lack of low-stress endorsements and presence of stress-word endorsements). Positive items for stress include, for example: “Tense”, “Uneasy”, and “Bothered”; negative stress items include: “Relaxed”, “Peaceful”, and “Cheerful”. Replication of similar results on British and Australian samples, two English-speaking countries with different histories and some variation in semantic content is offered by King, Burrows, and Stanley (1983) as evidence of usefulness and generalizability of the SACL instrument. In our sample of 69 participants, the SACL-A (start of the session) had internal consistency of $\alpha = .76$, the SACL-B (end of training portion), $\alpha = .88$, and the SACL-C (end of session), also $\alpha = .88$.

Procedure

Participants were directed by email prior to the participation in the main research session to complete a brief assessment of general cognitive ability through a link to the Wonderlic Personnel Test short form (WPT-Q, 30 items, 8 minutes timed). This was conducted on a secure site hosted by the Wonderlic Corporation. The first stage of participation involved questionnaires presented at a laboratory computer terminal.

Questionnaires related to intolerance of uncertainty, locus of control, coping style, and decision-making style.

Initial phase: preliminaries and explanations.

Participants were presented with a letter of information, offered the chance to ask questions, and given a two second sample of the white noise involved in the experiment. Levels were kept below 95 dB, the loudness of a subway train at 200 ft., consistent with our provincial labour standards and approved by institutional ethics review. Informed consent process was followed. After a brief introduction to the experimental apparatus, including roughly 2 minutes of practice on sample problems similar to experimental stimuli, participants were fitted with 10 electrodes, two on the neck, one in the pectoral area, and two along the lower rib cage, on both the left and right side. Several points of explanation were presented to the participants, as described, following. Electrodes were explained as disposable and discarded after use with only one participant. These electrodes were to be used to detect a physical signal, not to deliver a shock. Participants with more body hair were reassured care would be taken during removal of the electrodes to cause no more discomfort than the removal of a common adhesive bandage (such as a Band-Aid). All participants were fitted with a blood pressure cuff on their left arm. The blood pressure cuff intermittently inflated to take readings. Its design was explained as being such that a full, tight inflation would be necessary only at the beginning of the experimental sequence. Partial, differential inflation then allows calculation of blood pressure and there is no more discomfort after the initial tightness of a full inflation (as at a physician's office).

Second phase: Training and habituation.

The second phase involved answering decision scenario questions presented by computer. At this point, psychophysiological measurement equipment was applied to the participant. Once the electrodes, heart monitor, and blood pressure cuff was attached, the research assistant confirmed signal acquisition for calculation of relevant measures (stroke volume, cardiac output, total peripheral resistance, and heart rate acceleration/deceleration). Participants were instructed through a series of tutorial screens on the computer how to make selections in the decisional control paradigm, and reminded of white noise administration, with duration based on performance, at the end of the experiment. They were presented with 2 seconds of white noise as a mild aversive stimulus to motivate performance. The threat-oriented nature of this research supports the non-injurious, non-noxious use of a slightly aversive stimulus for paradigm validity. A set of "dummy trials" were presented to familiarize the participant with the apparatus and answering questions, after which the official hypothesis-oriented experimental data collection began.

Third phase: Decisional control experiment trials.

Each trial consisted of an initial baseline period. The word "Rest" appeared on the screen for 15 seconds, and the participant was instructed to sit back and take a relaxed, deep breath at this stage. Then, the computer screen showed the message: "Press and hold the Spacebar when ready". The participant pressed and held the spacebar, triggering the presentation sequence. First, a stressful vignette was presented. This included prompts at the end of the vignette asking three simple questions designed to raise stress levels,

focusing on consequences, people involved, and other situational features. Vignettes are included in the Appendix. An example of each type of vignette used is:

Credit Card Problem [Financial]

You are facing the loss of your credit card. This would also harm your credit rating. You need to make payment arrangements, and also manage future expense patterns. Your parents are the co-signers and they support half of your monthly payments. As such, they have an important say in what approach you can take, so this may limit your choices.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of losing your credit card?

Relationship Scenario [Social]

You are in a romantic relationship that means a lot to you. Your boyfriend/girlfriend has complained that you don't spend enough time together. You are working hard at school and other priorities, but this person is also important to you. Your romantic partner has conditions for you staying together, but you only have so much time to work with, and this may limit your choices.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of breaking up with your boyfriend or girlfriend?

Driving / Icy Roads [Physical]

It is a winter night and you need to get home. The roads are icy, winding and hilly. You are concerned about getting into an accident. You must make some important decisions about the way to get home, and how fast to drive. You are on the outskirts of town, and some roads have been closed, so this may limit your choices.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of having an accident?

Participants were instructed to keep depressing the spacebar as the scenario was presented, make a selection mentally, and then and only then remove their finger to press another key endorsing a specific selection on the screen. The experimental aim is to measure the time for information processing as separately as possible from the time for the visual-motor activity of choice registration.

A total of fifty-four trials were presented, with randomized ordering. These arose from the 9 x 6 choice structure by parameter pair design described in the Introduction. The convention for presenting choice type was a green box for Choice, a grey box for Uncertainty, and a series of red boxes for No-choice, with a single green box indicating the external selection given to the decision-maker at the No-choice level.

Presentation conventions were consistent with those used to represent the same constructs in the study reported in Chapter 4. The Uncertainty condition however, and the grey box

convention used to depict it, were not part of the Chapter 4 experimental Choice Structure conditions.

Under UC scenarios, putative choices of elements under ‘Choice’ are made. The first response (selecting the best available element, in advance) was used as the comparative decision-making time RT1 with other choice structure responses. For paradigm consistency, participants nonetheless continued making all possible putative selections, in order of preference, until an ordered preference of p elements (one element per bin potentially-assigned under Uncertainty) were completed. Considerations of paradigm veracity were deemed likely to influence participant response, in requiring more information processing under UC than under NC, for example.

Proxy depiction of threat via two-letter pairs.

Each scenario’s sets of elements were populated by letter-pairs, such as “CJ” or “QR”. These were explained as ranked according to alphabetical order, from left to right for letter ordinal positioning, as in a dictionary. These letter-pairs were necessary to populate the parameter pair scenarios where (p, q) were $(5, 7)$ and $(9, 7)$, as the 26 letters of the English alphabet would be insufficient to depict 35 and 63 discrete threat levels, respectively. These proxy stimuli were used as requiring some degree of evaluation (allowing for ‘decision-making time’), but as having a specific canonical ordering. Excluded from the list of all possible pairs of 26 letters were all stimuli beginning with A- or Z-, as too easily processed as best or worst in ordinal ranking. Also eliminated were letter pairs with commonly perceived semantic content such as “BE”, “IQ”, or “IT”, to

prevent confounding of processing by inadvertent processing of meaning, irrelevant in this decision-making context.

Supportive study for subjective perception of threat by two letter proxies.

Important to note with regard to these letter-pairs is the extensive work of the third author, Melanie King, who conducted a distinguished honours thesis investigation of the threat perception of a comprehensive sample of these letter-pairs. This thesis (King, 2013) was able to uncover situations of ‘stretch’, ‘compression’, or ‘leapfrogging’ in the distance and ordering of participant perception of letter-pairs. She accomplished this by Thurstonian psychological scaling of threat perception of the two-letter stimuli in a large undergraduate sample, using established methodology (Torgerson, 1958; see especially Chapter 9, “Law of Categorical Judgments”).

Some effects this study found included the perception of letters nearer to the beginning and end of the alphabet in a more canonically anchored way (closer to ‘dictionary ordering’) than letters in the middle range. She also reported (King, 2013) that the second position letter could have an undue influence, beyond simply playing the ‘tie-breaker’ when identical letters were found in the first position. This was more pronounced with second letters found towards the end-points of the alphabet, especially with first-position letters in the middle range of alphabet positioning (e.g., J to S). For example, the letter-pair perceived as least threatening in her sample of 160 stimuli was “CB”, with a very low scaled value of 0.08; a few rank positions lower, “BD”, at a 0.58 scaled value, which should have been in first place in this sample. Again, “KG” (scale value, 1.18) ranks ahead of “FZ” (scale value, 1.34), as another example.

Despite this interesting variation, ordering of stimuli was on the whole, correct, such that participant perception of letter-pairs as proxies for an ordered set of threat values is considered paradigm-valid. The correlation of participant Thurstonian-scale values with canonical ordering was $r = 0.94$ for the 160 letter-pairs selected by stratified sampling. For example, 'BH' had a scale value of 0.53 (for threat perception as harmonized with across participant response sets), and a canonical position or 'dictionary ordering' of 34; 'HN' had a scale value of 1.33 and a canonical position of 196, and 'XF', 3.04 and 604, respectively). With regard to letter-pair use in the main study, an alphabet ranking task of ten words with a comprehensive range of starting letters was used to ensure prior participant knowledge of alphabetical order. Three participants did not pass this task, and their data was also removed from the analysis.

The methodology used by King (2013) assessed subjective perception of threat when comparing letter-pairs to a sample of recently viewed letter-pairs together and then presenting them individually, asking for a ranking from 1 to 9 for likelihood of triggering the undesirable event described in a stress vignette. The subjective aspect of the perception of threat as transmitted through these letter-pair proxies was the objective of this methodologically rigorous study. However, in the main study, participants were not asked to follow their impressions, but a clearly instructed and made to practice a deliberative process, using the 'dictionary order' priority ranking for the two-letter pairs.

Stress ratings.

Subsequent to each trial, after the participant released the spacebar (ending the 'decision-making time') and entered the two-letter pair selection made, they were also prompted to

enter a stress rating for the previous trial. Specifically, they were asked to rate on a 1 to 5 Likert-type scale how stressful they had found the previous trial: 1 - "Not at all", 2 - "Slightly", 3 - "Moderately", 4 - "Considerably", and 5 - "Extremely".

Performance feedback and debriefing.

There is a "correct" response for all scenarios presented and a simple yes/no count was kept of correct responses. With a view to providing gently aversive response motivation, the participant was given from 0 to 10 seconds of white noise at a controlled decibel level (approved by Ethics review as non-harmful) over computer speakers to create ecological validity with stress negotiation scenarios. Performance was evaluated such that 100% correct answers corresponded to 0 seconds of white noise, 90-99% correct - 1 second, 80-89% - 2 seconds, and so on, with 0-9% correct corresponding to 10 seconds of white noise. Experimenters reported no administrations longer than 5 seconds were given.

After computer trials were completed, the participant was given a debriefing letter and a receipt for participation, and signed their names in acknowledgment of this receipt. They were offered a copy of this record, and one copy was kept on file.

Results

Results are reported under several headings and subheadings below. Psychometric and demographic data are first presented, with specific scales and values. Correlations are then presented for context and background. Following this, a sizeable section is included that calculates 'method data', or quantities deriving from theoretical formulations.

Finally, results of testing for Hypothesis I, Hypothesis II, and for a possible Theoretical Synthesis are presented.

Psychometric and Demographic Data

Wonderlic Personnel Test – QuickTest (WPT-Q).

WPT scores range from 1 to 50; a score of 25 is considered equivalent to an IQ score of 100 for the same population. Participant scores for the WPT were normally distributed ($N = 67$, $M = 25.1$, $SD = 3.6$; range: 18 to 33). For two participants, test values were not considered valid due to timing out of the online session.

Intolerance of Uncertainty Scale (IUS).

Scores on the Intolerance of Uncertainty Scale have a theoretical range of 27 to 135. Scores were normally distributed ($N = 69$, $M = 62.0$, $SD = 17.2$, range: 28 to 107).

Ways of Coping scales (WC).

The Ways of Coping Inventory generates scores on eight scales for styles of coping. The eight scales can be computed based on a community sample or student sample. For this research, we used the student sample calculation, with student-specific sets of items for each particular scale's calculations. All 69 participants had valid values for the eight scales, and all were normally distributed.

Internal Control Index (ICI).

The Internal Control Index yields a single score estimate of disposition towards an internal locus of control. The theoretical minimum and maximum for the 28 item 5 point

Likert-type scale are 28 and 140 respectively. Scores were normally distributed ($N = 69$, $M = 97.9$, $SD = 12.6$; range: 71 to 123).

General Decision-Making Scale (GDMS).

The Decision-Making Scale yields a score for five styles of decision-making. In the original scale publication (Scott & Bruce, 1995), one item was missing, for the Rational scale: “I explore all of my options before making a decision.” (as reported by Appelt, Milch, Handgraaf, & Weber, 2011; note, the present study was designed prior to 2011). Our research was conducted with 24 of the 25 items on the scale, five items for each scale, but with four items on the Rational decision-making style scale. Scores on all five scales were distributed normally. A novel calculation was also made, the sum of all endorsements. The measure, the GDMS aggregate, was used as an indicator of a tendency to identify highly with several decision-making styles.

Stress Adjectives Checklist (SACL).

Scores on the Stress Adjectives Checklist were compiled for time points A (start of the session), B (start of the experimental trials), and C (end of the experiment). Adding positive and negative items (dichotomous scoring) yielded normally distributed scores for all six sets of nine positive and negative nine items at time points A, B, and C. This alternate scoring method, suggested by Cruickshank (1984), dichotomizes the scale between endorsement and no endorsement. Because of the nature of the two non-endorsement levels (‘not sure, don’t know’ and ‘definitely not’), the numerical meaning most supportive of this semantic content is ‘0’. As such, scores were re-calibrated as “1”

or “0” for endorsement or no endorsement for the upper two levels and lower two levels of responses, reverse coded for positive (non-stressful) items.

Correlations

In Table 3, below, a pattern of significant moderate to high moderate *negative* correlations occurs between the Internal Control Index (ICI) and several measures, namely: the General Decision-Making Scale (GDMS aggregate, $-.57$), GDMS-Dependent ($-.52$), GDMS-Avoidant ($-.61$), and to a lesser degree, the GDMS-Spontaneous ($-.30$), GDMS-Intuitive ($-.26$), as well as the Ways of Coping-Wishful Thinking scale (WC-WT, $-.44$), WC-Self-Blame (WC-SB, $-.32$), and the WC-Detachment scale (WC-D, $-.25$), and the Intolerance of Uncertainty Scale ($-.32$). This list of correlations supports the construct validity of internal control, in that it relates negatively with several indices often considered maladaptive, whereas a strong sense of internal control is considered adaptive (see Duttweiler, 1984). By contrast the ICI correlates significantly to a moderate *positive* degree with WC-Problem-focused [coping] (WC-PF, $.38$), cognitive ability (WPT-Q, $.26$), and to a high moderate positive degree with the GDMS-Rational scale ($.53$). Each of these is consistent with standard expectations from the internal control construct. Interestingly, there is a significant weak moderate correlation between ICI and Age, such that younger participants are tending to report higher internal control.

Table 3

Correlation among Psychometric Variables

	IUS	ICI	GDM S	GDM S-R	GDM S-I	GDM S-D	GDM S-A	GDM S-S	WPT- Q	Age	Sex	WC- PF	WC- WT	WC- D	WC- SS	WC- FP	WC- SB	WC- TR
ICI	-.32																	
GDMS	<u>.24</u>	-.57																
GDMS-R	.20	.53	<u>-.25</u>															
GDMS-I	-.03	<u>-.26</u>	.68	<u>-.26</u>														
GDMS-D	.19	-.52	.67	-.19	.32													
GDMS-A	<u>.30</u>	-.61	.75	-.38	<u>.27</u>	.40												
GDMS-S	-.04	<u>-.30</u>	.62	-.37	.44	.12	<u>.29</u>											
WPT-Q	-.04	<u>.26</u>	-.16	.20	-.07	-.17	-.10	-.19										
Age	.10	<u>-.27</u>	-.06	<u>-.25</u>	.05	-.15	.00	.09	-.03									
Sex	-.09	.14	.03	-.05	.04	<u>-.24</u>	.02	<u>.27</u>	<u>.30</u>	.09								
WC-PF	.10	.38	-.06	.40	.14	-.15	<u>-.29</u>	.00	-.07	-.05	.07							
WC-WT	.37	-.44	.47	-.04	.22	.33	.43	.21	-.04	-.03	.10	.18						
WC-D	<u>.25</u>	<u>-.25</u>	.44	.07	.19	.22	.32	.32	-.06	.05	.13	.04	.46					
WC-SS	.23	-.23	<u>.29</u>	.04	<u>.31</u>	.32	.18	-.06	-.10	.05	<u>-.25</u>	.23	.43	.12				
WC-FP	.05	.20	.04	<u>.25</u>	.05	-.04	-.10	.10	-.10	.08	.06	.57	.16	.08	<u>.26</u>			
WC-SB	.35	-.32	.47	-.03	<u>.24</u>	.32	.43	.18	-.05	-.10	.02	.17	.65	.22	.43	.23		
WC-TR	.20	-.10	.13	.19	-.04	.08	.07	.09	-.04	-.01	.19	<u>.27</u>	.34	.17	.19	.34	.22	
WC-KS	<u>.28</u>	-.14	.19	.11	-.03	-.08	.19	<u>.30</u>	-.05	.11	.20	.14	.38	.43	-.10	<u>.24</u>	.16	.23

Underline indicates $p < .05$ (2-tailed); **Boldface indicates $p < .01$ (2-tailed).**

IUS: Intolerance of Uncertainty; ICI: Internal Control Index; GDMS: General Decision-Making Scale (full score aggregate), -R: Rational, -I: Intuitive, -D: Dependent, -A: Avoidant, -S: Spontaneous; WPT-Q: Wonderlic Personnel Test-QuickTest; Sex is coded as male, 1, female, 0; WC-PF: Ways of Coping-Problem-Focused, -WT: Wishful Thinking, -D: Detachment, -SS: Seek Social Support, -FP: Focus on the Positive, -SB: Self-Blame, -TR: Tension Reduction, -KS: Keep to Self [bottom row].

In Table 3, notable significant correlations occur between the aggregated score of the General Decision-Making scales and measures often considered maladaptive: WC-Wishful Thinking, WC-Detachment and WC-Self-Blame; note this aggregate correlates highly with four of the five GDMS separate scales, but to a weak though significant degree with the GDMS-Rational scale. It appears the four ‘other’ decision-making styles, Intuitive, Avoidant, Dependent and Spontaneous, are not as desirable in relation to coping styles considered more adaptive. There appear to be both a passive and an agentic ‘cluster’ of variables, with other variables retaining a mixed set of associations. The passive cluster, conceivably more maladaptive, loads especially on measures of wishful thinking, avoidant decision-making, detachment, self-blame, and high aggregate ratings on multiple decision-making styles, suggesting identification with multiple styles; these measures also correlate negatively with an internal control disposition.

The converse profile in Table 3 associates high internal control, rational decision-making, problem-focused coping, and a focus on the positive in what appears by canonical standards in personality psychology as a more adaptive cluster of preferences and personality features. Note that control variables of Age, Sex, and cognitive ability (WPT-Q) are not significantly correlated to any other psychometric measures at the $p < .01$ level (no **boldface type** values for control variables). This indicates that these potential nuisance variables are likely not introducing a major confounding effect.

Experimental stress measures (SACL).

The Stress Adjective Checklist data was used as a secondary indicator of proneness to stress reactivity. Scoring was done as per Cruickshank’s (1984) method of allotting one

‘stress point’ for actual endorsement (high or moderate) of stress words (e.g., “Tense: definitely yes”, or “Bothered: slightly yes”), and a ‘stress point’ for ignorance or denial of non-stress states (e.g., “Calm: don’t know/not sure”, or “Peaceful: definitely not”). The other two points on the response scales received a zero towards the total summation (reverse scored for positive stress-related phrases, such as Calm, Peaceful, or At Rest).

Table 4

Correlations for Time A, B, and C on Stress Adjective Checklist, including subscales

	SACL-A	SACL-B	SACL-C	SACL-neg. A	SACL-neg. B	SACL-neg. C	SACL-pos. A	SACL-pos. B
SACL-B	<u>.28</u>							
SACL-C	.23	.50						
SACL-neg. A	.69	.07	.05					
SACL-neg. B	.07	.78	.35	.12				
SACL-neg. C	.11	.39	.77	<u>.25</u>	.49			
SACL-pos. A	.82	.32	<u>.26</u>	.15	-.01	-.06		
SACL-pos. B	.38	.89	.48	.01	.41	.20	.49	
SACL-pos. C	<u>.30</u>	.45	.88	-.09	.14	.37	.48	.57

Underline indicates $p < .05$ (2-tailed); **Boldface indicates $p < .01$ (2-tailed).**

In examining Table 4, above, values for the Stress Adjective Checklist are within expectations and support confidence in experimental proceedings. Stress endorsed at three time points, A, B, and C are correlated to suitable degrees. Time-point A represents the start of the experiment. Time-point B represents the end of the training periods, which were of 10 to 20 minutes duration. Time-point C represents stress after all experimental trials of the same list of 18 stress-related words. The measures reported in Table 4, above, include the positive and negative facets only (nine words of each kind), together with their summed measure, scored such that a higher value indicates more stress.

As seen in Table 4, the three time-points appear to be suitably inter-related. Stress ratings at entry (SACL-A) and after training (SACL-B) are significantly correlated to a low moderate degree (.28). Stress at entry and endpoint shows no significant correlation (.23, not significant). Stress at the end of training (SACL-B) and at the end of the experiment (SACL-C) show a high moderate correlation (.50). Both the negative and positive facets correlate highly with the overall scales at all time-points; the positive stress-related words show a higher magnitude correlation with their associated full scale than the negative, but all magnitudes are high. Outside of sub-scale affiliated scores for the same time-point (e.g., A, positive A, negative A), the best predictors of stress between time-points were between time-points B and C (end of training, end of experiment) for non-endorsement of positive stress-related words (e.g., “Calm”, “At Rest”, “Relaxed”). These scores involved coding with a ‘stress point’ if participants either did not know or were unsure, or did not experience these subjective states. Similar magnitudes appear for the negative endorsements and overall scales, such that stress at time-point B, after familiarization with the decisional control paradigm is the best predictor of stress at time-point C after completion of decisional control trials.

Decisional Control Method Data

Response set size (*RSS*).

Response Set Size for the nine decision scenarios in our study are shown in Table 5. These values represent the number of possible responses for the participant in each decision-scenario, or, Choice Structure by Parameter Pair experimental cell condition.

Table 5

Response Set Size by decision scenario

Scenario	$RSS(p, q)$	$RSS(2, 2)$	$RSS(7, 2)$	$RSS(4, 3)$	$RSS(4, 5)$	$RSS(5, 7)$	$RSS(9, 7)$
CC	pq	4	14	12	20	35	63
CN	p	2	7	4	4	5	9
CU	p	2	7	4	4	5	9
NC	q	2	2	3	5	7	7
NN	1	1	1	1	1	1	1
NU	1	1	1	1	1	1	1
UC	q	2	2	3	5	7	7
UN	1	1	1	1	1	1	1
UU	1	1	1	1	1	1	1

Probability of the Lowest Threat Option (Pr(t1)).

Probability of Lowest Threat Option for the nine decision scenarios are shown in Table 6.

It is calculated by dividing Response Set Size (RSS) by the factorial Element Set Size ($fESS$). Factorial Element Set Size is the full number of elements in a scenario, in first-order scenarios, $fESS$ has a value of pq (bins x elements), as opposed to Element Set Size (ESS), the number of elements in a given bin, with value q .

Table 6

Probability of Lowest Threat Option by decision scenario

Scenario	(p, q)	$(2, 2)$	$(7, 2)$	$(4, 3)$	$(4, 5)$	$(5, 7)$	$(9, 7)$
CC	pq / pq	1.000	1.000	1.000	1.000	1.000	1.000
CN	p / pq	0.500	0.500	0.333	0.250	0.143	0.143
CU	p / pq	0.500	0.500	0.333	0.250	0.143	0.143
NC	q / pq	0.500	0.143	0.250	0.250	0.200	0.111
NN	$1 / pq$	0.250	0.071	0.083	0.050	0.029	0.016
NU	$1 / pq$	0.250	0.071	0.083	0.050	0.029	0.016
UC	q / pq	0.500	0.143	0.250	0.250	0.200	0.111
UN	$1 / pq$	0.250	0.071	0.083	0.050	0.029	0.016
UU	$1 / pq$	0.250	0.071	0.083	0.050	0.029	0.016

Outcome Set Sizes (OSS).

Table 7 below shows Outcome Set Sizes for the experimental cell conditions.

Table 7

Value for Outcome Set Size in 9 x 6 experimental cell conditions

Scenario	(p, q)	$(2, 2)$	$(7, 2)$	$(4, 3)$	$(4, 5)$	$(5, 7)$	$(9, 7)$
CC	pq	4	14	12	20	35	63
CN	p	2	7	4	4	5	9
CU	pq	4	14	12	20	35	63
NC	q	2	2	3	5	7	7
NN	1	1	1	1	1	1	1
NU	q	2	2	3	5	7	7
UC	pq	4	14	12	20	35	63
UN	p	2	7	4	4	5	9
UU	pq	4	14	12	20	35	63

Mathematical Expectation of Threat ($E(t)$).

In Table 8, below, the mathematical expectation of threat $E(t)$ is depicted. These values are calculated using a standard vector of threat value with equal increments.

Table 8

Mathematical Expectation of Threat $E(t)$ by decision scenario

Scenario	(2, 2)	(7, 2)	(4, 3)	(4, 5)	(5, 7)	(9, 7)
CC	0.2000	0.0667	0.0769	0.0476	0.0278	0.0156
CN	0.3333	0.1250	0.2000	0.2000	0.1667	0.1000
CU	0.4000	0.3000	0.3846	0.4286	0.4444	0.4375
NC	0.3333	0.3333	0.2500	0.1667	0.1250	0.1250
NN	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
NU	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
UC	0.3333	0.3333	0.2500	0.1667	0.1250	0.1250
UN	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
UU	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000

Note, see Chapter 2 – Appendix, p. 56, for formulations of $E(t)$ by p and q .

Threat-Exposure (TE) and Decision-Making Value (DMV).

Threat-Exposure TE is a metric derived for the first time in Chapter 4 (see p.136-139). In this context, this study was not designed to evaluate for this new metric, but as the same paradigm is used, an approximate comparison can be made between procedures used in Chapter 4 and the same procedures used on nearest comparable levels of decision scenarios within this chapter (Chapter 5). The Threat-Exposure metric was twinned with Information-Processing Demand to obtain a Threat-Control Expenditure, which can be inverted to provide an indication of Decision Value. Decision Value was found in Chapter 4's study to be a valuable, entirely theoretical, predictor of participant behaviour

in terms of time spent on decisions, reduction in heart rate indicative of increased information intake (akin to ‘focusing’), and a higher proportional endorsement of a given trial with higher ‘Decision Value’ as stressful, controlling (as the derivation of Decision Value does) for the size of the sets being evaluated.

Threat-exposure was calculated as the exposure to post-scenario negotiation threat per unit of control afforded by the scenario (see Chapter 4). The calculation for TE is calculated as $E(t) / Pr(t_1)$. Information Processing Demand was calculated as the amount of discrete items of information to be processed per unit of unit of control offered by a scenario, and is obtained by the formula $RSS / E(t)$. This study was not designed to test these metrics, so limited evaluation of possible hypotheses will be made to indicate whether some level of replication is possible. However, as detailed further below in ‘Future Investigations’, worthy prospects exist for evaluating the addition of Uncertainty and the associated use of OSS in metric calculations.

In order to evaluate this new metric in a way comparable to its original formulation, two sets of similar parameters were selected. In the original study (see Chapter 4), the choice structures of CC, NC, and NN were used. The parameter pair values of (2, 2) and (2, 4) were the variation in set sizes. In the present study, two pairings were selected as comparable to the original pair of parameter set sizes. First, (2, 2) and (7, 2) was chosen as a pairing that retains (2, 2) as a parameter pair, and includes an unchanging parameter. In this case, parameter q stays constant at 2. Given that these measures use proportions, it is reasonable also to attempt to maintain a similar pq product, newly defined in this study as the factorial Element Set Size, $fESS$, above.

Secondly, (4, 3) and (4, 5) were chosen as existing experimental levels on which to test the newly developed metric for Decision Value, as it retains the same bin values ($p = 4$) for both pairings, just as the original study did ($p = 2$, for (2, 2) and (2, 4)). Additionally, these are also the lowest available pq product values, or *fESS* values, in order to maintain a similar range to minimize effects due to scale that may occur with larger pq values, such as with the largest two parameter pairs in this study, (5, 7) and (9, 7). In particular, it must be recalled that it is a human decision-maker upon whom this cognitive demands are being made, and as such, different processes and individual preferences may emerge as larger sets of evaluations are required for scenario navigation. This may be expected with fatigue, working memory limitations, and other frustrations or strategies incompatible with larger number of cognitive evaluations.

In Tables 9 and 10, below, Threat-exposure and information-processing demand are calculated for the (2, 2) and (7, 2) and the (4,3) and (4,5) parameter pairings, respectively, according to the method outlined in Chapter 4.

Table 9

Threat-exposure, information processing demand for (2,2), and (7,2) scenarios

Scenario	TE	<i>(2, 2)</i>	<i>(7, 2)</i>	IPD	<i>(2, 2)</i>	<i>(7, 2)</i>
CC	$E(t)/Pr(t_1)$	0.200	0.067	RSS/E(t)	20	210
NC	$E(t)/Pr(t_1)$	0.667	2.333	RSS/E(t)	6	6
NN	$E(t)/Pr(t_1)$	2.000	7.000	RSS/E(t)	2	2

Table 10

Threat-exposure and Information Processing Demand for (4, 3) and (4, 5) scenarios

Scenario	TE	<i>(4, 3)</i>	<i>(4, 5)</i>	IPD	<i>(4, 3)</i>	<i>(4, 5)</i>
CC	E(t)/Pr(t ₁)	0.077	0.048	RSS/E(t)	156	420
NC	E(t)/Pr(t ₁)	1.000	0.667	RSS/E(t)	12	30
NN	E(t)/Pr(t ₁)	6.000	10.00	RSS/E(t)	2	2

The values in Tables 9 and 10, above, are proportionalized to allow for comparability across different parameter sets, for ranges that are near one another. This method allows for comparison between the stress deriving from Threat-Exposure, in its relative allotment between different decision scenarios, and the stress deriving from Information-Processing Demand, as allotted similarly by different decision scenarios. This method works in particular because all participants have responded to each cell condition trial. As such, relative perceptions of scenarios close in parameter ranges are potentially comparable.

The procedure for deriving the proportion scores are to sum values across the 3 x 2 experimental conditions, then divide each cell value by this sum. The result represents the share of ‘Threat-Exposure’ or of ‘Information Processing Demand’ that is allotted to this experimental cell condition as it relates to its 5 other comparable structural and parameter neighbours. This calculation is depicted as $TE / \Sigma TE$ and $IPD / \Sigma IPD$ in Tables 11 and 12.

Table 11

Proportional Threat-exposure, Information Processing Demand for (2, 2) and (7, 2)

Scenario	TEp	<i>(2, 2)</i>	<i>(7, 2)</i>	IPDp	<i>(2, 2)</i>	<i>(7, 2)</i>
CC	TE / ΣTE	0.01630	0.00544	IPD/ ΣIPD	0.08130	0.85366
NC	TE / ΣTE	0.05435	0.19022	IPD/ ΣIPD	0.02439	0.02439
NN	TE / ΣTE	0.16304	0.57065	IPD/ ΣIPD	0.00813	0.00813

Note in Table 11, above, how the proportion of Threat-Exposure (TE_p) is allotted most heavily to the NN(7,2) condition, and the proportion of Information-Processing Demand (IPD_p) is heavily weighted towards CC(7,2). This is consistent with the expectation and the intent of these new constructs.

The verbal interpretation of the proportion of Threat-Exposure values is as follows. First, the CC conditions show the least exposure to threat. This is consistent with the CC structure providing the most decisional control, and associated threat-reduction. Second, the trend from CC to NC to NN is for an increase in Threat-exposure. This is construct-valid, in terms of the NN condition requiring the most tolerance of post-scenario threat, CC the least, and NC an intermediate amount. Finally, examining the Threat-Exposure columns on the left (for (2,2) and on the right (for (7,2), the trend where 'N' is present is an increase in threat-exposure, the trend at CC, with no 'N', is a decrease in threat-exposure. This is consistent with the 'C' condition reducing threat, and the 'N' condition leaves threat at a maximum.

The verbal interpretation of the proportion of Information-Processing Demand values is as follows. First, the CC conditions show the highest proportion of Information Processing Demand. This is construct-valid, as two 'C' nodes require the most cognitive operations to identify the lowest threat option. Second, the trend is for a decreasing proportion of Information Processing Demand from the CC to NC to NN choice structures. This is also construct-valid. Finally, although NC and NN show the same values for proportion of Information Processing Demand, across (2, 2) and (7, 2), CC increases considerably. This is model-consistent, in that the number of elements to evaluate (RSS) are 4 and 14, respectively, while the expectation of threat ($E(t)$) decreases

by a factor of 3, from 0.2000 for (2, 2) to 0.0667 for (7, 2). That is, the ultimate ‘threat’ faced in the wake of scenario negotiation is lower in the case of (7, 2) than it is in the case of (2, 2), and the concept in this framework is that this lower absolute threat expectation engenders decreased motivation to furnish the higher number of mental operations. This construct is new, and scaling is not expected to be exact. Further rounds of experimentation are needed for refinement of this methodology. However, what is confirmed is the *direction of expected effects*, whereby participant behavior is expected to mirror patterns in the theoretically modelled constructs calculated in Tables 9, 10, and 11 above, and Tables 12, 13, 14, 15, and 16, below. This direction of expected effects follows certain trends that can be approximated by verbal description, but the pattern of expected effects can potentially be obtained by following the theoretically modelled properties and the procedure outlined. When relevant cognitive processes driving participant responses are well-approximated by model structure and settings, unusual or apparently idiosyncratic changes in trend lines can be predicted in an explicable manner at a level more intricate than linear or quadratic curvilinear trendlines only.

Table 12

Proportional Threat-exposure, Information Processing Demand for (4, 3) and (4, 5)

Scenario	TEp	(4, 3)	(4, 5)	IPDp	(4, 3)	(4, 5)
CC	TE / Σ TE	0.00432	0.00268	IPD/ Σ IPD	0.25080	0.67524
NC	TE / Σ TE	0.05621	0.03747	IPD/ Σ IPD	0.01929	0.04823
NN	TE / Σ TE	0.33725	0.56208	IPD/ Σ IPD	0.00322	0.00322

The values in Table 12, above, can be observed to follow a pattern similar to that in Table 11. Notable difference are threefold. First, an attenuation in the proportion of Information-Processing Demand for the CC(4, 5) condition (IPDp = 0.675) in

comparison to the CC(7,2) condition ($IPD_p = 0.854$). This is consistent with a reduced differential between the p and q values for the (4, 3) and (4, 5) combination as compared with the (2, 2) and (7, 2) combination. Second, the effect of changing q values (3 and 5, instead of being held constant at 2) can be observed to lower the value for the proportion of Threat-Exposure between the (4, 3) and the (4, 5) parameter pairs for both the CC and NC conditions. Finally, the Information-Processing Demand can be observed to increase in the NC condition between the (4, 3) and (4, 5) conditions, by contrast to no change under NC between (2, 2) and (7, 2). This is again construct valid, since the number of responses possible is higher where q increases (in this case, from 3 to 5) under NC. This occurs because Choice ‘C’ at the element level yields more decisional control with a larger number of choices at that level. With increased number of elements-per-bin ($q = 5$, instead of $q = 3$), NC demands increased information processing, but it is also more powerful for threat reduction. This concomitant threat reduction can be observed by comparing NC(4, 3) and NC(4, 5) values for proportion of Threat-Exposure (0.0562 and 0.03747).

Table 13

Threat-Control Expenditure and Decision-Making Value (2, 2) and (7, 2)

Scenario	TCE	(2, 2)	(7, 2)	DMV	(2, 2)	(7, 2)
CC	avg.(TEp,IPDp)	0.04880	0.42955	(1-TCE)	0.95120	0.57045
NC	avg.(TEp,IPDp)	0.03937	0.10730	(1-TCE)	0.96063	0.89270
NN	avg.(TEp,IPDp)	0.08559	0.28939	(1-TCE)	0.91441	0.71061

In Table 13, above, the Threat-Control Expenditure is reported. Threat-Control Expenditure is intended as an index of threat-exposure and control efforts, and as such summarizes essentially in one metric the basic need for a decisional control model.

Threat-Control Expenditure indexes the cost of threat-reduction currency in the economy of probabilistic threat, valuing equally the demands of information processing and threat exposure. Notably, it is sensitive to interactions between choice structure and number of choices. For example, when comparing CC, NC, and NN with parameter pairings (2, 2) and (7, 2), as in Table 13 above, CC(7, 2) assumes a considerable share of the Threat-Control Expenditure, in relation to NC(7, 2) and NN(2, 2), whereas CC(2, 2) assumes a share comparable to NC(2,2) and somewhat lower than NN(2, 2).

Also in Table 13, above, Decision-Making Value is included. In previous research (see Chapter 4), Decision Value was the ultimate focus of the metrics developed. Note that in the present study, it is renamed here to Decision-Making Value in order to avoid confounding the acronym DV with a 'dependent variable'. Decision-Making Value has also been set aside as a primary metric, in favour of Threat-Control Expenditure. This saves the process of inverting the Threat-Control Expenditure, which can add its own change in substantive meaning. There are already several stages of transformations in this approach. It was also felt by the first author, the designer of these metrics, that the decisional control model has had a long-standing focus on controlling threat, rather than on illustrating decision-making value. These quantities are quite closely related, but the consistency with fundamental paradigm priorities for Threat-Control Expenditure was considered greater than Decision-Making Value. A new avenue of research is open if threat values are converted to utility values, and obtaining some tangible 'good' becomes the new focus of the probabilistic description of flow of likelihoods in hierarchical structures. As such, an unreduced figure for Decision-Making Value (simply $1 - \text{TCE}$, without removing 'bulk' by removal of excess area under the trendline, as in Chapter 4)

is provided in Tables 13 and 14. By contrast, Threat-Control Expenditure as a quantity is ideally minimized when the aim is threat- or stress-reduction, and is considered by our research team a valid focus for a single decisional control metric, in present and incipient research programs.

Table 14

Threat-Control Expenditure and Decision Value (4, 3) and (4, 5)

Scenario	TCE	(4, 3)	(4, 5)	DMV	(4, 3)	(4, 5)
CC	avg.(TEp,IPDp)	0.12756	0.33896	(1-TCE)	0.87244	0.66104
NC	avg.(TEp,IPDp)	0.03775	0.04285	(1-TCE)	0.96225	0.95715
NN	avg.(TEp,IPDp)	0.17023	0.28265	(1-TCE)	0.82977	0.71736

In Table 14, above, patterns that are observed in other tables are also seen. Notably, the NC structure appears to demand the least combined expenditure of Threat-exposure and Information-Processing Demand. As well, the (4, 5) parameter pairing appears more ‘expensive’ in terms of expenditure of threat tolerance and mental effort than the (4, 3) parameter pairing. Although this difference is least pronounced under the NC structure, where ‘C’ at the element level gives near-parity for the (4, 3) and (4, 5) pairings, nonetheless, the sensitivity of the model to interacting quantities provides a predicted superiority to the (4, 3) condition that is at the very least intriguing. The quantitative nature of this prediction is open to empirical test, and will be tested in the Theoretical Synthesis subsection within this same Results section, further below.

Table 15

Threat-Control Expenditure by Choice Structure

Scenario	TCE	Sum (2,2),(7,2)	Sum (4,3),(4,5)
CC	Σ TCE(CC)	0.47835	0.46652
NC	Σ TCE(NC)	0.14667	0.08060
NN	Σ TCE(NN)	0.37498	0.45288

In Table 15, above, the pattern of expectations for Choice Structure alone, summing the results of the parameter value pairings, yields similar predictions for both the (2, 2) and (7, 2) pairing, and the (4, 3) and (4, 5) pairing. A considerably lower Threat-Control Expenditure is predicted for the NC condition, and a higher Threat-Control Expenditure is predicted for the CC and NN conditions, as per the values in Table 15, above. This should be evident in a ‘dip’, or conversely, a ‘spike’ in empirical results for stress-related measures at the NC condition, as compared to CC and NN conditions, where similar stress-related values are expected.

Table 16

Threat-Control Expenditure by Parameter Pair Values

Scenario	TCE	(2, 2)	(7, 2)	(4, 3)	(4, 5)
Avg. (CC, NC, NN)	TEp + IPDp	0.17376	0.82624	0.33554	0.66446

In Table 16 above, the last of this series of tables illustrating the Threat-Control Expenditure procedure, the pattern of expectation for Parameter Value pairings alone is presented. Values are summed across CC, NC, and NN, and are presented as the proportion of Threat-Control Expenditure (the full expression of this quantity) that is attributable exclusively to the Parameter Value pairing, as it relates to its proportional

‘seat-mate’, where two pairs have been twinned to apportion a share of threat exposure and information processing demand. Note that the values sum to a full 1.0 value across the two parameter value set pairings, namely, across (2, 2) and (7, 2), and also to a 1.0 value across (4, 3) and (4, 5). These are the expectancies for the effect of parameter values, collapsed across choice structures. In previous research associated with that reported in Chapter 4, choice structure was shown to have a significant effect, but parameter values less so. Although collapsing was not reported in Chapter 4, the information directly available in table form in Chapter 4 supports an expectation for an independent effect of Choice Structure on Threat-Control Expenditure. Evidence supporting an independent effect for Element Set Size (the name of the variable used to refer to a change in the value for q in that previous study) exists, but is weaker. This evidence includes a larger effect size for Choice Structure than for Element Set Size ($\eta_p^2 = .45$ and $\eta_p^2 = .40$, respectively), and analyses with collapsed values not reported in Chapter 4, but apparent in the information presented in its tables.

Decision-making time data.

The values for Decision-Making Time were observed to be distributed over a wide range. Because a wide variety of decisional control scenarios were presented, inclusiveness for outlying values was the pre-determined bias. When low values occurred (below 100 ms), consideration was given to whether this was a ‘fast responder’, who had several other fast RT1 values (i.e. five or more); consideration was also given to the type of trial with low RT1, if a rapid decision was expected in such scenarios (specifically, NN scenarios of low pq product, such as NN(2,2), NN(7,2)). If either case was true, the value was kept in

order to permit comprehensive exploration of a new range of experimental values. When high values occurred (exceeding 20,000 ms), the type of decisional control scenario and response properties in similar scenarios (e.g., CU(5, 7), CU(9, 7))were considered. Overall, less than 10 deletions were made in the dataset of 54 scenarios by 63 participants with valid Decision-Making Time data. This procedure was somewhat satisfactory, but did not systematically integrate all conditions under a single rule.

Ultimately, the decision rule adopted for each of the empirical quantities (RT1, STRSS, and HRDEC) was to establish a z-score for each value in the entire sample of participants on a given condition. A z-score of less than 5 was the criterion for inclusion within the data set for that condition (e.g., RT1 times for CN(7,2)). The resulting pruning was favourable both to the removal of egregious outliers (RTs of several minutes), but preserved intact the unique features of given conditions, where several high or low values might be observed (i.e, high RTs under CU (9,7), and low RTs under NN (7,2)). For RT1, a floor of 100 ms was maintained and a ceiling of a z-score of less than +5.0.

Subjective Stress Ratings.

Subjective stress ratings were registered by participants after each trial. These were rated from 1 to 5 from “Not Stressed at All” to “Extremely Stressed”. Ratings ranged from an lowest average of 1.46, in the NU(9, 7) condition, to a highest average of 2.58 in the UU(9, 7) condition. Participants reported lower stress, possibly associated with a kind of ‘relief’, when faced with NU and reported higher stress when faced with UU, possibly associated with an innate sense of work, effort, or compounding

uncertainty, generally. This pattern held across other parameter set values, also. Within the 5.0 z-score rule, no outliers were detected.

Psychophysiological data.

Indications in previous research (see Chapter 4) have been that heart rate deceleration (HRDEC), also known as minimum heart rate, is significantly affected by changes in decisional control independent variable levels. Other psychophysiological measures can be examined, but HRDEC in particular has shown sensitivity to choice structure and element set size. It is one of the key markers, with Decision-Time (RT1) and Single-Trial Rating of Subjective Stress (STRSS), of Threat-Control Expenditure within the context factorial administration of decisional control cell conditions. Outliers were determined via the +/- 5.0 z-score rule, and values deviating from the mean (above or below) were deleted in order starting with absolute distance from the mean, followed by deletion of a value at the other end of the distribution if the dynamically updated maximal absolute z-score was still higher than 5.0.

Heart Rate Deceleration was calculated by subtracting minimum heart rate during a rest period of 15 seconds from minimum heart rate during task completion. Intervening between the two was a 16 second 'stress prompt' period, with standardized vignette presentation and three standardized stress-inducing questions. As such, a baseline level of stress is established by use of the rest period for each trial, standard stress-induction is presented, randomly selected across 9 possible vignettes, and a standardized, timed presentation of three short stress-related questions (focusing attention on Who?, What?, and How?) were presented. Difference in minimum heart rate reactivity between

decision-making time and rest period are expected to relate to increased information intake during the decision-making time.

Hypothesis I

The first major hypothesis involved evaluating the predicted *strong correlation with decreasing trend* between $Pr(t_1)$ and $E(t)$ as indicated in Table 1 in the introductory section, roughly in concert with increasing pq or, factorial Element Set Size $fESS$.

Results indicate that there is partial support for Hypothesis I, with certain disconfirmations of expected results. Namely, the expected strong negative correlation of probability of access to the least threatening option $Pr(t_1)$ with empirical proxies of expected threat $E(t)$ showed partial confirmation on the HRDEC and RT1 measures, and no support on the STRSS measure. The partial confirmations with HRDEC and RT1 were in the expected range and direction for each of parameter pairs (7, 2), (4, 3), (4, 5), and (5, 7). Parameter pairing (2, 2) showed no significant correlation ($r = 0.10$; $R^2 = 0.01$, or 1 % of variance accounted for) between $Pr(t_1)$ and RT1. As seen in Table 17, the RT1 measure showed the expected trend in the intermediate values (non-extreme pair values). These fell in a pattern, for (7, 2), (4, 3), (4, 5), and (5, 7), of 64%, 71%, 67%, and 42% of variance accounted for. Model expectancies, as in Table 1 (introductory section for this chapter), were 80%, 70%, 60%, and 50%, respectively. For its part, the (9, 7) pairing showed a renewed strength of correlation, instead of a decrease (e.g., % variance accounted for of 55%, up from 42% for (5, 7)). Between (7, 2) and (5, 7), the four parameter value sets show a similar strength of association to that theoretically expected, and a generally decreasing trend in this association. Removing the upper and lower ends

of the 6 parameter pair test, and allowing for differences in scaling for the association, the trend and approximate strength is confirmed to be in line with theoretical predictions.

This rudimentary but promising alignment will be returned to in the Discussion. The HRDEC values (reactivity scores), show a strong relation in the first parameter pair level (2, 2), but then taper to a largely stable percentage of variance accounted for of approximately 20 %, more or less, through all other parameter pair levels. It might be speculated to future investigative profit that a combination of the RT1 and HRDEC measures might combine to equal the $E(t)$ expectancy column more closely.

Table 17

Percentage of variance accounted for by $Pr(t_1)$, by parameter pair value

	$E(t)$	RT1	STRSS	HRDEC
(2, 2)	91%	1%	3%	71%
(7, 2)	80%	64%	0%	18%
(4, 3)	70%	71%	1%	20%
(4, 5)	60%	67%	2%	24%
(5, 7)	50%	42%	1%	12%
(9, 7)	40%	55%	0%	19%

Interpreting Table 17 and the results of Hypothesis I, it appears that RT1 is somewhat consistent with the pattern of expected threat $E(t)$ as it relates to $Pr(t_1)$, except at the (2, 2) parameter pair value level. The STRSS variable appears to have no relation to the $Pr(t_1)$ variable, and the HRDEC variable has some degree of relation to the $Pr(t_1)$ variable, especially at the (2, 2) experimental level, and in a stable way through other levels for parameter pair values.

An important addition must also be made by reporting the correlations between theoretical properties $Pr(t_1)$ and $E(t)$ and empirical measures RT1, STRSS, and HRDEC-

Task. These are calculated over 54 bivariate pairs of theoretical expectancies or cell means across all participants.

Table 18

Correlations between theoretical quantities and empirical measures

	Pr(t ₁)	E(t)	RT1	STRSS	HRDEC
Pr(t ₁)	---				
E(t)	-.70	---			
RT1	.45	-.43	---		
STRSS	-.12	-.03	.26	---	
HRDEC	-.28	.38	-.57	-.74	---

The arrangement of correlations between quantities and averaged cell condition measures is a promising indication of relations between several of these indices. Significance values can be estimated, but should not be interpreted in the same way as with raw data that is free to vary with experimental error. Theoretical values and averaged cell values tend to exclude error. Nonetheless, that pattern indicates that

1. Pr(t₁) and E(t) are being calculated correctly, their correlation is expected
2. RT1 is the experimental measure most linked to Pr(t₁) in this sample
3. E(t) and RT1 vary inversely
4. HRDEC and E(T) vary positively, together
5. RT1 and HRDEC vary inversely to a high moderate degree
6. HRDEC and STRSS vary powerfully and inversely, despite STRSS not relating to the theoretical quantities

These findings, although somewhat unexpected, can nonetheless be interpreted theoretically and inform theoretical refinements and modifications.

Hypothesis II

The second major hypothesis involved the evaluation of the effect of subordinate uncertainty in decisional control hierarchies. This was tested using the same empirical proxies for stress as for the first hypothesis: HRDEC, RT1, and STRSS.

Planned contrasts.

Again, results show partial and valuable confirmation, with certain qualifications and some disconfirmations. The four predictions evaluated regarding the presence of an uncertainty node were as follows:

- a. Stress for CU > Stress for UC
- b. Stress for CN < Stress for CU
- c. Stress for CC < Stress for NN
- d. Stress for NN = Stress for UU

The first two predictions (a. and b.) use the stress measures (HRDEC, RT1, and STRSS) directly to contrast recorded stress levels for the listed conditions (CU and UC, CN and CU). Note that HRDEC has been found to operate in tandem with RT1 and STRSS, but in the opposite direction. Accordingly, testing is arranged in an opposite direction for the HRDEC measure, but in support of the same expected effect. The second two predictions (c. and d.) contrast ‘pure choice type’ scenarios, namely CC with UU and NN with UU, according to model expectations that use the mathematical expectation of threat, also called expected threat $E(t)$ as the driver for expectation of participant stress. These comparisons are included for the valuable opportunity to test and potentially refine model assumptions for sources of threat and stress.

The support or lack of support from testing with each of the three dependent measures is listed in Table 19, below.

Table 19

Expected Stress	RT1	p of H_0 (or H_1)	STRSS	p of H_0 (or H_1)	HRDEC	p of H_0 (or H_1)
CU > UC	Support	10^{-54}	(sig.opp.)	(0.0000003)	not sig.	0.60
CN < CU	Support	10^{-49}	Support	0.0006	Support	0.001
CC < NN	(sig.opp.)	(10^{-47})	(sig.opp.)	(0.0003)	(sig.opp.)	(0.0001)
NN = UU	(sig. diff.)	.004	(sig. diff.)	(10^{-16})	(sig. diff.)	(0.000007)

Table 19 displays the answer to the Uncertainty Effect prediction, the second major hypothesis in this investigation. The answer is: yes, the Uncertainty Effect is empirically measurable, but it is localized especially to the CN-to-CU comparison. Using RT1 as a proxy for stress, the CU-to-UC comparison is powerfully vindicated. With the other two stress proxy measures, results are in the opposite direction (STRSS) or not significant (HRDEC). Other expected variations due to placement of the Uncertainty condition have little or no support, or support *for the opposite direction of effect*, as shown with results in parentheses in Table 19.

Means for each of the conditions listed in Table 19 are visually depicted in Figures 5.1, 5.2, and 5.3, below. A visually noteworthy pattern in these figures, a type of ‘scallop-shape’ for the C and U bin-choice segments, is detailed further below.

Figure 5.1

Reaction Time Mean Values, by Choice Structure, with 95% C.I. Error Bars

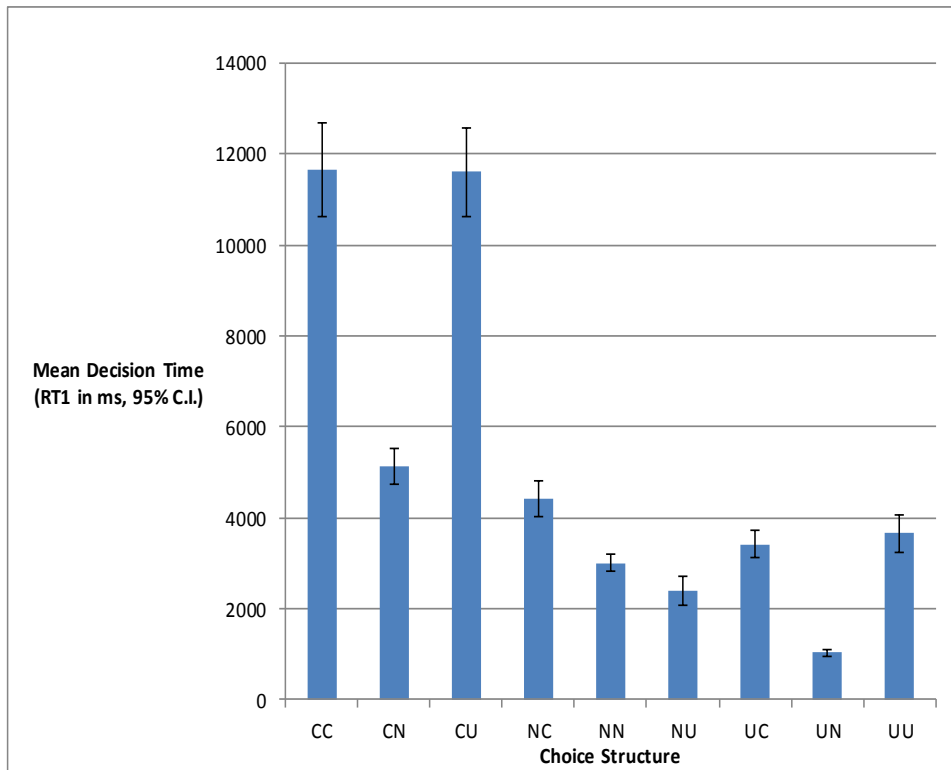


Figure 5.2

Stress Rating Mean Values, by Choice Structure, with 95% C.I. Error Bars

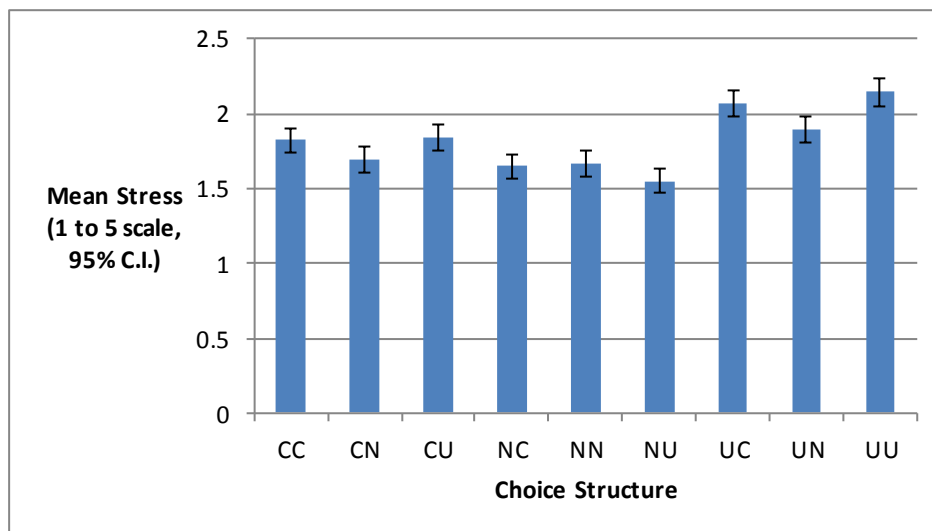
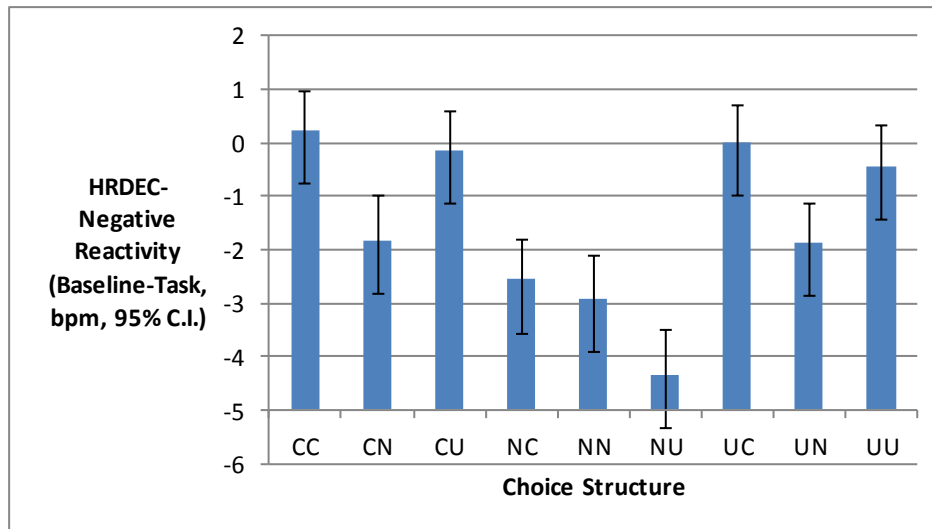


Figure 5.3

Negative Reactivity for HRDEC, by Choice Structure, with 95% C.I. Error Bars



Figures 5.1, 5.2, and 5.3, above, are best explained as a group. All three figures depict the three dependent measures of special interest in this study as collapsed across the six levels of Parameter Pair Values in the experiment. What remains are the column-wise means for Choice Structures only. These means are calculated over a maximum of 426 individual values (6 x 71) and a minimum of 368 values (426 minus outliers and missing data) for the three dependent measures, supporting accurate reflection of Choice Structure variation. Error bars for 95% confidence interval, calculated on a *t* distribution are depicted for each column. The calculation of Figure 5.3 values is done simply inverting the sign of the HRDEC-Reactivity score. This yields the HRDEC-Negative Reactivity score, and allows for variation to be compared in alignment with the variation in RT1 and STRSS, as above and also presented in Chapter 4 of this dissertation volume. Note that the horizontal-axis for Figure 3 is placed at -5, to allow all values to register in a positive

direction. The aim is to allow clearest visual comparison in variance between the three dependent measures across the three figures.

What is most striking to our research team with these graphs is the ‘scalped shape’ of the CC, CN, CU, and again UC, UN, UU segments of the Choice Structure column graphs in all three figures. These are highly pronounced on Figure 5.1 for the Decision-Time values, but are meaningfully present (and statistically significant, as per Planned Contrasts, below) in Figures 5.2 and 5.3. There is very little overlap between error bars for the ‘scooped’ or ‘scallop-shaped’ formations made by CC, CN, and CU, and UC, UN, and UU on Figures 5.2 and 5.3. In addressing the planned contrasts below, the CN to CU comparison can be placed in the context of Figures 5.1, 5.2, and 5.3, above. For its part, the NC, NN, and NU segments of each figure show no consistent pattern across the three figures, and error bars can be seen to overlap considerably.

Theoretical Synthesis

Values for Threat-Control Expenditure.

Expected values for Threat-Control Expenditure are listed in for the 3 x 2 experimental conditions in Tables 13 for the (2, 2) and (7, 2) pairing and Table 14 for the (4, 3) and (4, 5) pairing. Values aggregated for Choice Structure only and for Parameter Value Sets only are listed in Tables 15 and 16, respectively.

The respective data for comparison using the three stress proxies (HRDEC, RT1, and STRSS) are listed below, and compared the proportion of Threat-Control Expenditure values. For the HRDEC values, neither proportions nor patterns align in an expected way

with predictions. Looking at a main effect level, CC values for HRDEC are a single digit percentage of proportional values, whereas NC and NN take up 40% to 50%, or 50% and 40% of the proportions in an alternating pattern (for the (2, 2)-(7, 2) pairing and (4, 3)-(4, 5) pairing, respectively). For the Parameter Pair level analysis, proportions collapsed across choice structures result in an apportioning of 53%-46% for (2, 2)-(7, 2), and 54%-46% for (4, 3)-(4, 5). These allotments bear little resemblance to the expected balances of 17%-83% and 34%-66% for the same two sets of parameter pair value pairings. This result is disappointing in that it is negative, but scientifically valuable as a correct instantiation of a method in very early stages of development and so a useful negative finding.

Discussion

Hypothesis I: Chance of Lowest-threat-option Predicts Decreased Total Threat

Hypothesis I: 'Best-option' and 'total threat' correlation attenuates.

The confirmation of an expected attenuation in the percentage of variance in stress, whether $E(t)$ theoretically or RT1 and HRDEC empirically, accounted for by availability of the best option, $Pr(t_1)$, is a vindication of a bold model prediction. To recap, between the four intermediary parameter set values of (7, 2), (4, 3), (4, 5), and (5, 7), a downward-trending progression is observed for the duration of decision-making measure (RT1). Even adding the last of six pair levels, (9, 7), remains within this general trend (though at 55%, showing a slight upswing). Only the (2, 2) pair value seems not to fit the trend at all (at 1%, or a negligible relation). The HRDEC measure (reactivity in minimum heart rate between task performance reading and baseline reading) shows a bi-modal downward

trend where the (2, 2) pair level shows a high percentage of variance in stress (as measure empirically by *decrease in HRDEC*) accounted for by availability of the best option – $Pr(t_1)$ – at 71%; as the square of the correlation coefficient, this is evidence of a powerful connection. The remainder of the pair levels show a fairly steady association anchored around an average value of 18.6%, with a maximum of 24% at (4, 5) and a minimum of 12% at (5, 7). Despite not obtaining perfect or close replication of theoretical predictions (a neat 10% descending sequence across the six parameter-pair levels), retrieving a similar pattern from a large sample of laboratory participants is akin to finding long lost relatives in whom a touch of family resemblance reassures the parties involved of some degree of common genesis. These two empirical progressions are doing the same thing as the theoretical progression, for what appears to be some of the same reasons. Two of three dependent measures support the trend. Parcelled out more specifically, 11 of 18 experimental predictions are associated with empirical results within trend-admissible expectations (excluding all of STRSS and (2,2) on RT1). With these results, there is good though imperfect support for validity in the prediction, the method, and the model.

Hypothesis I: ‘Best shot’ as ‘overall odds’ – implications and applications.

In a more practical vein, the upshot of this research may encourage, with appropriate accounting of the influence of branching set sizes, assessment of threatening situations by rapid evaluation of the likelihood of obtaining a ‘best option’. If a ‘best option’ has a low chance of being obtained, a sound heuristic can conclude that the likelihood of threat overall – the chance of an untoward outcome – is greater. Depending on the context, it may be wisely considered a more dangerous, hostile, or unaccommodating environment.

As a nod to the effect of symbols with possible interaction with a ‘availability of best option’ heuristic, the ascendance to the U.S. presidency of a man of black African heritage (President Barack Obama in 2009) may well boost the confidence of all African Americans, and minority populations generally, in the *possibility* of attaining the highest levels of leadership. If the ‘best option’ heuristic can be shown to work in a *utility* sense, where chance at a positive outcome is the mindset, then a symbol like an African-American president provides a broad revision for tens of millions of people of the expectancies for good options in their own lives. In mathematical terms, a single positive instance is incalculably more of a statistical factor than no tangible instances at all. One in a million is something, still. Zero in a million is nothing at all.

Specific estimates and heuristics can be made with the decisional control model, as in Studies 2 and 3. Some examinations of the attenuation effect confirmed in this study have revealed that ‘bottleneck’ formations, whereby either p or q is minimized to 3 or ideally, 2, with the other value maximized, create the most leveraged situations for linking $Pr(t_1)$ and $E(t)$ in their association. Conversely, a ‘wide, even spread’ heuristic, where p and q are as close in value as possible, together with a larger product value pq , tends to attenuate the negative correlation of $Pr(t_1)$ and $E(t)$ the most.

One example of a potentially application can be found in a simple game of marbles. Assuming each marble has a unique rank (ordinal value), if a child has 20 marbles and he must expose them in groups to competition from his rival, then the child who would maximize his total rank does well to divide his marbles into 4 piles of 5 marbles each, and play first for access to a pile, randomly populated, then allow the winner to pick freely from a pile of 5. If an ambitious player is looking to draw down his rival’s total

rank of marbles, he does well to suggest the game be structured in two piles of 10 marbles, or alternatively, 10 piles of two marbles each, assuming all piles are played for to obtain selection access. This ‘bottlenecking’ allows for selection from a larger set, and most powerfully, the excluding of a larger number of lower value marbles with each hard-won selection. Statistically, the attenuation expected, in terms of percentage of variance accounted for by the correlation of $Pr(t_1)$ and $E(t)$ is a progression from 82% and 79% for (2, 10) and (10, 2), respectively, down to 60% and 59% for (4, 5) and (5, 4). Note, (4, 5) and its expected percentage of variance accounted for (60%) is an experimental level for Hypothesis I. Given the partial support of results in our experiment, the above allotments might well find their confirmation in measured stress levels in the competitors.

Hypothesis II: Uncertainty Effect Holds in Experimental Trials, with Qualifications

Hypothesis II: Choice is hampered by subordinate node uncertainty.

In terms of subordinate positioning of uncertainty, contrasting UC and CU, there is only support for more stress at CU using the RT1 measure. In terms of the uncertainty choice type as compared with the no-choice choice type, the model, there is consistent support across the three measurement modalities (RT1, STRSS, HRDEC) that stress levels are higher for participants in negotiating a CU scenario than a CN scenario.

When considering the CU condition, certain features are valuable to highlight. In general, a ‘maximax’ approach to selection has appeared to be effective in reducing overall situational threat. Indeed, this approach helps lower expected threat $E(t)$ in all but the CU structure where there is decisional control to be had. Unfortunately for the maximizing

decision-maker, a CU structure negotiated with a maximax strategy confers very little benefit for threat reduction over full entropy conditions (NN, NU, UN, UU). This occurs because the decision-maker is opting for t_1 under a maximax strategy, but there is no account of its bin-neighbours, who may represent any value from t_2 to t_{pq} in the sequence of threat values. With the other decision structures containing at least one choice node, healthy elimination of some or all undesirable t values can occur. Under CU, with choice of bin and deferred assignment of element-within-the-bin by an external decision-making agency after bin selection has been made, the decision-maker is left to opt for t_1 without regard for the subset of t values that are co-nested with it. Under UC, by contrast, p putative choices of element, one per bin pending deferred assignment of bin, allows the input of p selections worth of ‘whittling’ down the possibilities. This is what makes UC identical to NC in $E(t)$ calculation, though the mechanisms are different. To evince the value of UC fully: even if t_1 ’s bin is not eventually selected, the best option t in each of the $p - 1$ other bins has been identified and ‘queued up’, so to speak, pending deferred external assignment. A practical counsel to the decision-maker facing a CU scenario might be: select the bin with the lowest average indexing value i (for example, t_1 ’s indexing value is $i = 1$). More thoroughly, if possible, selecting the lowest average bin value for all t values present is the best bet.

The relevance of the above discussion, in light of our study’s findings, is that these expectations do manifest themselves in measurement of participant behaviors. A new study might contrast participants’ stress levels in CU scenarios for one group instructed on a maximax technique and a second group instructed to select by bin average.

The CU consideration is operative even in the previous section. It may be noted that when exactly equal dispersion of p and q is not possible (as with the example of a pq product of 20), the correlation and attendant percentage of variance accounted for decreases slightly when bin number p is the higher of the two numbers that cannot be identical. This occurs for the (5, 10) and (10, 5) pairs, and again, slightly for the (4, 5) and (5, 4) pairs in the preceding section. This attenuation is due to CU underperforming, somewhat, as part of the average value across nine conditions, whereas UC, its matched pair is not underperforming. For CN and NC, the advantage is perfectly counterbalanced when p and q both can be the superior number to the same extent. For CU and UC, however, UC always has the proverbial “upper hand”; again, under the maximax assumption.

Hypothesis II: Model revisions – Uncertainty and No-choice differ.

The uncertainty and no-choice conditions have been shown to differ considerably in the stress recordings they evoke in participants. This is an important source of information for updating the decisional control model. The mathematical expectation of threat, or expected threat $E(t)$, is the anchor point theoretical proxy for the stress levels that decision-making for threat-reduction is expected to elicit. Until now, the uncertainty and no-choice conditions were “mathematically equivalent” in most scenarios. The CU asymmetry, revealed in simulation work, has also now been given partial support experimentally. Although CN and CU operate in the expected relation (with CU resulting in higher stress levels), it appears in examining CC, NN, and UU results that much more is at play in evoking stress from participants under uncertainty than the objective statistical properties of threat reduction they are facing. Proxy stress measures, for CC,

NN, and UU, appear in several instances to be behaving, in our experiment data and sample, in a way *opposite to that expected*. This reversal of expectations is an important, valuable, and needed though perhaps humbling contradiction of model expectancies. Nonetheless, because the model is rigorous, and specifications were, in a word, *specific*, this result can correct wrong assumptions and point clearly to new territory for investigation should the model continue to be refined.

Decision Value

The novel approach to Decision Value did not replicate in the new analyses. This study was not designed for replicating the Chapter 4 results. Nonetheless, if such a replication were designed, it appears that a closer control and more cautious extension is in order. Many factors play into extending this approach. It may be that the Chapter 4 abductive reasoning mechanism is a ‘lucky strike’ on a true phenomenon. If so, it may take delicate work to replicate it under conditions that imitate and perhaps extend the original experiment only slightly. This is referred to in Chapter 1 as the “titrating” necessary for mathematical modeling work to be effective: a laborious process of minute adjustments.

Once the right balance is found, the various components being modeled can be incorporated without prejudice or to the exclusion of other quantities or components. Until then, a peaceful order for co-existence of known relevant variables has not established a system where relative impacts can be harmonized to depict and predict some semblance of real-world phenomena. Inspiration and further ideas for components of such improved modeling may be found, for example, in related work on the dynamics of daily stress as measured by diary sampling (Levy, Yao, et al., 2012).

The Decision-Value approach, use of a Threat-Control expenditure to explain participant stress *and* attraction to perceived high-return decisions stands to be a useful notion, the specifics of which remain to be determined. The use of a proportions approach herein, although convenient, may erase some irresolvable feature of dimensional units that may prove to be key component for modeling motivation to engage in decision-making.

Whatever the cost, our choices define who we are as human beings. A sensible, simple, effective theory for decision-making appeal is something of potential benefit to all sentient beings. Appreciation of statistical context for decision-making can bring clarity to dilemmas faced in the course of living. The authors' hope is that wounded persons with distorted decision-making skills might helped in starting to heal non-normative habits that impair the sustenance of suitable well-being for themselves and many others.

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5.3 Comment on “Decisional Control Modeling (...)”

The manuscript presented points to several potentially fruitful avenues of inquiry, and indicates caveats important to maintain in exploratory research. Varying parameters along fine distinctions is a well-established practice in cognitive psychology, a field with which these approaches share considerable common ground. The results reported narrow the predictions made by purely theoretical means towards zones of intermediate independent variable levels. These are the zones where model properties apply the most, experimentally, in the way they are expected to function, theoretically. In general terms, this study has found some vindication, and has exposed gaps in the interlock between theoretical expectation and experimental observations.

5.4 Appendix for “Decisional Control Modeling (...)”

Financial

1) Loss of Scholarship.

You are facing the prospect of losing your entrance scholarship. This money is important for financing your education. You must make some important decisions for bringing up your marks up, meeting athletic commitments and doing community service. Teachers, coaches, and supervisors have some say what strategies are available, and this may limit your choices.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of losing your scholarship?

2) Credit Card Problem

You are facing the loss of your credit card. This would also harm your credit rating. You need to make payment arrangements, and also manage future expense patterns. Your parents are the co-signers and they support half of your monthly payments. As such, they have an important say in what approach you can take, so this may limit your choices.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of losing your credit card?

3) Job Loss

You have a part-time job on campus. You need this income. Your boss is unhappy with your work. You are in a demanding program and the hours of study required are affecting you job performance. You will have to make important decisions to maintain an

income and get good grades. Your boss and your teachers have clear expectations, so this may limit your choices.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of losing your job?

Social

1) Reputation / Peer Pressure

You attend a party with people in your program. You are invited to take part in an offensive drinking game. You are not a drinker but if you don't participate, you will probably not be included in future activities. You need to make decisions about behaviour, friends and social life. Social opportunities are few in your program, so this may limit your choices.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of a poor quality social life?

2) Relationship Scenario

You are in a romantic relationship that means a lot to you. Your boyfriend/girlfriend has complained that you don't spend enough time together. You are working hard at school and other priorities, but this person is also important to you. Your romantic partner has conditions for you staying together, but you only have so much time to work with, and this may limit your choices.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of breaking up with your boyfriend or girlfriend?

3) Public Speaking

You are preparing for an end-of-term class presentation. You must get an 'A' grade to get the mark you need from this course. Other students have expressed doubt about your abilities in this course. You must choose a topic, do research, and deliver a presentation. Your instructor must approve your topic and presentation format, so this may limit the choices you can make.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of not making the grade you need?

Physical

1) Workout Injury

You work out regularly to keep in shape. You sprained your ankle recently, but without exercise, your mood and thinking skills deteriorate. If you continue exercising, there is a real risk of re-injury. You need to make decisions about a way to exercise. Your workout partner has preferences, and the fitness centre is being renovated, so your options may be limited.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of re-injuring yourself?

2) House Emergency

The house you share with 3 roommates is old and poorly maintained. During a cold snap in January, you wake up in the middle of the night, and the furnace is broken. You have an in-class exam in the morning and you need to get some sleep. You need to

make decisions about sleep, getting help, and a plan. Your roommates have a say, so your choices may be limited.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of missing or failing your exam?

3) Driving / Icy Roads

It is a winter night and you need to get home. The roads are icy, winding and hilly. You are concerned about getting into an accident. You must make some important decisions about the way to get home, and how fast to drive. You are on the outskirts of town, and some roads have been closed, so this may limit your choices.

What is the worst that could happen?

Who will be affected the most?

How can you minimize your chances of having an accident?

5.5 Ethics for “Decisional Control Modeling(...)”

Note that original project title was “Decisional Coping Style”.



Department of Psychology The University of Western Ontario

Use of Human Subjects - Ethics Approval Notice

Review Number	10 12 04	Approval Date	10 12 14
Principal Investigator	Richard Neufeld/Matthew Shanahan	End Date	11 12 13
Protocol Title	Decision Coping Style		
Sponsor	n/a		

This is to notify you that The University of Western Ontario Department of Psychology Research Ethics Board (PREB) has granted expedited ethics approval to the above named research study on the date noted above.

The PREB is a sub-REB of The University of Western Ontario’s Research Ethics Board for Non-Medical Research Involving Human Subjects (NMREB) which is organized and operates according to the Tri-Council Policy Statement and the applicable laws and regulations of Ontario. (See Office of Research Ethics web site: <http://www.uwo.ca/research/ethics/>)

This approval shall remain valid until end date noted above assuming timely and acceptable responses to the University’s periodic requests for surveillance and monitoring information.

During the course of the research, no deviations from, or changes to, the protocol or consent form may be initiated without prior written approval from the PREB except when necessary to eliminate immediate hazards to the subject or when the change(s) involve only logistical or administrative aspects of the study (e.g. change of research assistant, telephone number etc). Subjects must receive a copy of the information/consent documentation.

Investigators must promptly also report to the PREB:

- a) changes increasing the risk to the participant(s) and/or affecting significantly the conduct of the study;
- b) all adverse and unexpected experiences or events that are both serious and unexpected;
- c) new information that may adversely affect the safety of the subjects or the conduct of the study.

If these changes/adverse events require a change to the information/consent documentation, and/or recruitment advertisement, the newly revised information/consent documentation, and/or advertisement, must be submitted to the PREB for approval.

Members of the PREB who are named as investigators in research studies, or declare a conflict of interest, do not participate in discussion related to, nor vote on, such studies when they are presented to the PREB.

Clive Seligman Ph.D.

Chair, Psychology Expedited Research Ethics Board (PREB)

The other members of the 2010-2011 PREB are: Mike Atkinson (Introductory Psychology Coordinator), David Dozois, Vicki Esses, Riley Hinson Albert Katz (Department Chair), and Tom O’Neill (Graduate Student Representative)

CC: UWO Office of Research Ethics

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6 Concluding Comments

This document has compiled advanced mathematical work, involved experimental apparatus, and abstract conceptions of mental work and personal motivation, with some success, into a compendium of approaches to decision-making under stress. As such, it is a volume that serves both as a chronicle of such research, and hopefully, a guidepost for similar avenues of inquiry.

In terms of validation, the mathematical modeling of decisional control continues to prove its worth, albeit with healthy pruning to account for ranges where fundamental assumptions apply to a greater extent, or where unanticipated phenomena impact participant stress to a pronounced or even dominant degree over model expectations. Participants were eager, keen, and capable. Research help was competent and trustworthy. The application of this highly abstract, theoretical, deeply principled work has been a joy, and in a properly scientific sense, a success. By informing judicious and normative hierarchical decision-making, our own research decisions have hopefully provided a somewhat satisfying outcome. We hope that future researchers interested in decisional control will benefit from our present revision of expectancies, and may themselves attain a set of not-too-undesirable outcomes, as well.

6.1 Statement of Originality

The work presented here is intended to delineate a new method for supplementing the experimental process, namely, rigorous modeling of the logic of decisional hierarchies and the attendant vigorous production of worthwhile research hypotheses. As such, the inaugural and painstakingly groundbreaking character of the work is offered in all scientific candor for consideration as part of the scholarly merit herein.

Curriculum Vitae: Matthew Jacques Shanahan

1 - Education

- 2007-** **Ph. D. candidate** in Clinical Psychology
Western University, London, Ontario, Canada
Thesis Supervisor: Dr. R.W.J. Neufeld
- 2005-2007** **Master of Science** in Clinical Psychology
Western University, London, Ontario, Canada
Thesis Supervisor: Dr. R.W.J. Neufeld
- 2002-2004** **Bachelor of Arts (Honours)** in Psychology, with Highest Honours
Carleton University, Ottawa, Ontario, Canada
Thesis Supervisor: Dr. Timothy A. Pynchyl

2 - Awards

- 2011** **Richard A. Harshman Memorial Scholarship**
Inter-departmental award for work in Statistical Methods – \$1000
- 2009** **London Regional Psychology Association (LRPA)'s Student of the Year** Collectively awarded to *Advocacy through Action* student group for library talk series “Finding Your Way”, February, London Public Library
- 2008** **Ontario Psychological Association (OPA) Public Education Award**
Collectively awarded to the *Advocacy through Action* student group for library talk series “Finding Your Way”, February, London Public Library
- 2008-2011** **Joseph-Armand Bombardier Canada Graduate Scholarship**
Social Science and Humanities Research Council of Canada (SSHRC)
Federal award – \$105,000 (\$35,000 for 3 years)
- 2007-2008** **Graduate Student Teaching Award** (top 1% of Teaching Assistants)
Institutional Award – \$500 - Western University
- 2007-2008** **Ontario Graduate Scholarship (OGS)** Provincial award – \$15,000
- 2006-2007** **Ontario Graduate Scholarship (OGS)** Provincial award – \$15,000
- 2005-2006** **Canada Graduate Scholarship – Master's level** – \$17,500
Social Science and Humanities Research Council (SSHRC)
- 2000-2001** **R.A. Wendt Prize for outstanding work in the History of Psychology**
Carleton University – \$325

3 - Publications

- Shanahan, Matthew J., Townsend, James T., & Neufeld, Richard W.J. (2015). Clinical mathematical psychology. In *The Encyclopedia of Clinical Psychology*, First Edition. Edited by Robin L. Cautin and Scott O. Lilienfeld. John Wiley & Sons, pp. 594-603. DOI: 10.1002/9781118625392.wbecp530
- Abbott, Kayleigh, Shanahan, Matthew J., & Neufeld, Richard W.J. (2013). Artistic tasks outperform nonartistic tasks for stress reduction. *Art Therapy: Journal of the American Art Therapy Association*, 30(2), 71-78. DOI: 10.1080/07421656.2013.787214
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- Shanahan, Matthew J., & Neufeld, R.W.J. (2010). Coping with stress through decisional control: Quantification of negotiating the environment. *British Journal of Mathematical and Statistical Psychology*, 63(3), 575-601. DOI: 10.1348/000711009X480640.
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4 - Conference Presentations (refereed)

- Shanahan, Matthew J. (2015, November). *Yes-No sieve for logical operators*. Poster presented at the Society for Judgment and Decision-Making (SJDM), Annual Conference, Chicago, Illinois, U.S.A.
- Neufeld, Richard W.J., Shanahan, Matthew J., & Nguyen, Peter. (2014, July). *Decisional control: A normative model of cognition-intensive coping with stress*. Paper, Society for Mathematical Psychology (SMP), 47th Annual Meeting, Quebec City, QC, Canada.

- Shanahan, Matthew J., Nguyen, Peter, & Neufeld, Richard W.J. (2012, July). *Coping with Stress through Decisional Control: The Mixture Model Side of a Quasi Game-Theoretic Account*. Paper, Society for Mathematical Psychology (SMP), 45th Annual Meeting, Columbus, OH, U.S.A.
- Abbott, Kayleigh, Shanahan, Matthew J., & Neufeld, Richard, W.J. (2012, June). *Something beautiful: Artistic tasks outperform non-artistic tasks for stress reduction*. Poster, Canadian Psychological Association (CPA), 73rd Annual Convention, Halifax, NS, Canada.
- Shanahan, Matthew J., Pawluk, Elizabeth J., Hong, Ryan Y., & Neufeld, Richard W.J. (2012, May). *Decisional-Coping Styles – Maximizing, Satisficing, Simplifying: Information Processing and Threat-Reduction, Threat-Mitigation, or Threat-Acceptance*. Poster, Association for Psychological Science (APS), 24th Annual Convention, Chicago, IL, U.S.A.
- Shanahan, Matthew J., Bruyns, Kaitlyn, Stewart, Shannon L., & Currie, Melissa. (2011, June). *Child/Youth and parent/caregiver experiences of intrusive measures during residential treatment for serious mental health issues*. Poster, 72nd Annual Convention, Canadian Psychological Association (CPA) in Toronto, ON, Canada.
- Shanahan, Matthew J., & Neufeld, R.W.J. (2010, August). *Mathematical expectation of threat, unpredictability, and mechanisms of stochastic "faint threat" in a model of decisional control*. Paper, 43rd Annual Conference, Society for Mathematical Psychology (SMP), Portland, OR, U.S.A.
- Shanahan, Matthew J. (2009, December). 'I can but I won't, I should but I don't ': Engaging students' personal barriers to implementing learning skills. *Self-Management Strategies and Successes*. Keynote speech, Learning and Study Skills Association (LASSA) Annual Conference, Hart House, University of Toronto, Toronto, ON, Canada.
- Shanahan, Matthew J., & Neufeld, Richard W.J. (2008, July). *Modeling cognitive load and threat reduction: Quantitative characteristics of hierarchically-nested decisional control scenarios*. Paper, 41st Annual Conference, Society for Mathematical Psychology (SMP), Washington, DC, U.S.A.
- Pawluk, Elizabeth J., Shanahan, Matthew J., Hong, Ryan Y., & Neufeld, Richard W.J. (2008, June). *Preference for Decisional Control Reflected in Situational and Individual Differences*. Poster, 69th Annual Convention, Canadian Psychological Association (CPA), Halifax, NS, Canada.
- Shanahan, Matthew J., Hong, Ryan Y., Pawluk, Elizabeth J., & Neufeld, Richard W.J. (2008, June). *Predicting stress: Comparing multimodal stress negotiation data to the predictions of a normative model of decisional control*. Poster, 69th Annual Convention, Canadian Psychological Association (CPA), Halifax, NS, Canada.

- Shanahan, Matthew J., & Neufeld, Richard W.J. (2007, June). *Modeling the interplay of cognitive load and threat reduction: An extensive investigation of the characteristics of hierarchically nested second-order decisional scenarios*. Poster, 68th Convention, Canadian Psychological Association (CPA), Ottawa, ON, Canada.
- Shanahan, Matthew J., & Neufeld, Richard W.J. (2007, May). *Statistical properties of a model for hierarchically nested second-order decisional scenarios*. Poster, 19th Annual Convention, Association for Psychological Science (APS), Washington, DC, U.S.A.
- Shanahan, Matthew J., & Neufeld, R.W.J. (2006, June). *Modeling the interplay of cognitive load and threat reduction across a range of decisional scenarios: A gold standard for quantifying the stresses of negotiating with the environment*. Poster, 67th Annual Convention, Canadian Psychological Association (CPA), Calgary, AB, Canada.
- Shanahan, Matthew J., & Neufeld, R.W.J. (2006, May). *Modeling the interplay of cognitive load and threat reduction across decisional scenarios*. Poster, 18th Annual Convention, Association for Psychological Science (APS), New York, NY, U.S.A.
- Shanahan, Matthew J., & Pychyl, T.A. (2005, June). *The relation of ego identity to self-reported procrastination among undergraduate students*. Poster, 66th Annual Convention, Canadian Psychological Association (CPA), Montreal, QC, Canada.

5 - Research Experience

- 2012-2013 Supervision, Honours Thesis – Scaling of Threat Perception**
Honours student: Ms. Melanie King; Co-supervisor, Matthew Shanahan; Supervisor, Dr. R.W.J. Neufeld, Western University
- 2012-2013 Program Review: “Building Families” Self-Care and Parenting Skills**
Supervisor: Dr. Jeff Carter, Vanier Children’s Services/Merrymount
Advisor: Ms. Wendy Tapp-Moore; Data analyst: Ms. Rachel Dean.
- 2010-2011 Supervision of Honours Thesis – Art-making for Stress Reduction**
Honours student: Ms. Kayleigh Abbott; Acting supervisor, Matthew Shanahan; Overall supervisor, Dr. R.W.J. Neufeld, Western University
- 2010-2011 Applied Research Practicum – Subjective Experiences of Restraint**
Supervisor: Dr. Shannon Stewart, Child and Parent Resource Institute (CPRI)
- 2010-2012 Dissertation Research: Decisional Coping**
Supervisor: Dr. R.W.J. Neufeld, Western University

- 2008-2009** **Supervision of Honours Thesis – Procrastination and Mental Health**
Honours student: Ms. Rebecca Stead; Acting supervisor, Matthew Shanahan; Overall supervisor, Dr. R.W.J. Neufeld, Western University
- 2007-2008** **Comprehensive Exam, Nonlinear Dynamical Modeling of Agency**
Supervisor: Dr. R.W.J. Neufeld, Western University
- 2007** **Psychophysiology of decision-making for threat reduction**
Supervisor: Dr. R.W.J. Neufeld; Collaborators: Ryan Y.S. Hong and Elizabeth J. Pawluk (Honours Student, co-supervised by M. Shanahan)
- 2005-2006** **Three-way ‘tensor’ approaches to Factor Analysis**
Course instructor: Dr. Richard A. Harshman, Western University
- 2005-2007** **Master’s Thesis – Decisional Control for Threat Reduction**
Supervisor: Dr. R.W.J. Neufeld, Western University
- 2004-2005** **Experiences of adults with late learning disability diagnoses**
Researcher: Dr. Timothy Farmer, Farmer and Associates
- 2003-2004** **Honours Thesis -- Ego Identity and Procrastination**
Research Supervisor: Dr. Timothy Pychyl, Carleton University
- 2002-2003** **The Qualities of a Hero: A Card Sort Procedure**
Research Evaluator: Dr. Chris Davis, Carleton University

6 - Clinical Experiences

- August 2013- July 2014** **Community Psychological Service. *Immaculate Heart of Mary Counseling Center.*** Catholic Social Services, Psychological Services. Lincoln, NE. Supervisor: Dr. Aaron Stratman. Intern within Nebraska Internship Consortium in Professional Psychology (NICPP), Catholic Social Services (CSS) site for psychology service delivery in a private, faith-based community organization.
- Summer/ Fall 2012** **Health Psychology. *Cardiac Rehabilitation Program,*** London Health Sciences Center, South Street Campus, London, ON. Supervisor, Dr. Peter Prior. Individual therapy in evidence-based cardiac rehabilitation setting.
- Winter/ Spring 2012** **Community/Group. *Merrymount Children’s Centre.*** London, ON. Supervisor, Dr. Jeff Carter, (off site at Vanier Children’s Services). On-site supervisor: Ms. Wendy Tapp-Moore. Return placement, specialization with “Building Families” psycho-educational group, teaching personal life skills and parenting knowledge for parents involved with child protection authorities.

- Fall 2009-
Spring 2010** **Outpatient.** *Operational Stress Injuries Clinic*, Parkwood Hospital, London, ON. Supervisor, Dr. Charles Nelson. Therapy, assessment, and group work with Armed Forces members and veterans, and Royal Canadian Mounted Police.
- Summer
2009** **Group / Health.** *Rheumatology Day Programs*, St. Joseph's Health Care, London, ON. Supervisors, Dr. Marilyn Hill and Dr. Warren Nielson. Progressively led most aspects of psychology role in Fibromyalgia group programs. Conducted assessments for rheumatology program admissions.
- Fall 2008-
Spring 2009** **Family-focused.** *Merrymount Children's Centre*. London, ON. Supervisor, Dr. Barrie Evans. Therapy with parents (grief, parenting, depression), therapy and assessments with children. Assisted with 6-month personal and parenting skills-building group for parents of children apprehended by local child protection authorities (Children's Aid Society - CAS). Community practicum pilot project under Interprofessional Health Education and Research initiative.
- Fall 2007-
Summer
2008** **Inpatient psychiatric.** *Regional Mental Health Care, St. Thomas Specialized Adult Services - Psychosis Unit*. St. Thomas, Ontario Supervisor, Dr. Rod Balsom. Assessment and therapy with acute and chronic psychosis patients. Some forensic work.
- Spring 2007** **Child Assessment.** *Child and Parent Resource Institute (CPRI)*. London, ON. Supervisors, Dr. Jeff St. Pierre and Dianne Shanley, M.A. Conducted full psycho-educational assessment for child with selective mutism.
- Spring 2007** **Adult Assessment.** *General Adult Ambulatory Mental Health Services (GAAMHS)*. London, ON. Supervisor, Dr. Louise Maxfield. Conducted assessment on client with PTSD and wrote DBT referral report.

7 - Professional Affiliations

- 2009-** Society for a Science of Clinical Psychology (SSCP) - Student affiliate
2008- Society for Mathematical Psychology (SMP)
2007- London Regional Psychological Association (LRPA)
2006- Association for Psychological Science (APS) – Graduate Student Affiliate
2005- Canadian Psychological Association (CPA) – Student Affiliate