4-2017

Examining a Normative Model of Stress Using Choice Under Risk

Zarmina Khan
zkhan92@uwo.ca

Examining a Normative Model of Stress Using Choice Under Risk

Zarmina Khan

Honors Psychology Thesis
Department of Psychology
Western University
London, Ontario, Canada
April, 2017

Thesis Advisors: Richard W. J. Neufeld, Ph.D. & Bryan Grant, M.Sc.

Abstract

Novel research in the domain of decisional control (DC), the process whereby individuals in multifaceted stressing situations make probabilistic judgments in order to reduce the occurrence of adverse events, has recently tested a mathematically specified normative model of coping with stress. This model used choice under uncertainty to understand the cognitive underpinnings of choice and linked threat. Findings from this undertaking have supported the notion that individualized subjective expected utilities (SEU) provide the best fit over group-averaged SEU and objective utility models in a sample of undergraduate students. The present research examined whether this finding holds true for choice under risk as well. Specifically, the game-theoretic probability mixture model used previously was tested using known probabilities of threat, rather than unknown probabilities of threat using the same methodology and a similar sample of undergraduate students. Psychometric profiling was also implemented to explore individual differences in DC amenability. A mixed-analysis ANOVA revealed that the three models, Individualized, Group, and Conditional, performed similarly under risk using two model-fit indexes, G^2 and Pearson χ^2. A correlation analysis also revealed individuals do not seem to differ on DC amenability based on the individual differences examined, but several variables appeared to correlate highly with one another.

Examining a Normative Model of Stress Using Choice Under Risk

The study of stress, particularly how humans respond to stressful situations, is a worthwhile endeavor, as experiencing and coping with stress are unavoidable aspects of everyday life. Given the significant and well-established role that stress plays in the onset and progression of numerous mental and physical illnesses (Dohrenwend, & Dohrenwend, 1974), understanding how individuals cope with stress can also elucidate clinical applications. According to Averill (1973), choice plays a fundamental role in how individuals respond to the various stresses they face. Through behavioral, cognitive, and decisional choice, individuals can access a range of alternatives available to them in a stressing situation (Averill, 1973). Having choice works to reduce threat and the stress associated with that threat, providing a decision maker (DM) with a sense of control. The focus of the present research is on decisional choice, specifically a normative model of coping with stress known as decisional control (DC) (Shanahan & Neufeld, 2010; Neufeld et al., 2014; Benn, 2002). In DC, an individual in a multifaceted stressing situation makes probabilistic judgments about the threats they face in order to minimize the probability of an adverse event occurring (Lees & Neufeld, 1999).

A greater number of options in a multi-option environment in turn provide DM's with a greater opportunity to exert DC, through an increased likelihood of finding a favorable option. However, the increased information processing needed to do so can be equally taxing on an individual's resources, as DC is a cognition-intensive process (Solomon et al., 1980; Kukde & Neufeld, 1994). More information processing may be required to reach the most optimal decision when the number of potential options is increased, which can create further stress in an individual. For example, consider an individual with social anxiety that finds him or herself in a large social gathering such as a birthday party. The individual has many options of who to interact with, and can thereby choose to approach a person who seems the least intimidating (e.g. someone who they have met before who smiles at them from across the room). This process of evaluating the threat associated with each social encounter however requires a significant amount of thought and attention, which can cause further stress and dread due to its cognitively intensive nature. On the other hand, having limited options, or no options at all can be less cognitively taxing on a DM due to the reduced amount of information processing. However, this scenario may result in the individual experiencing the worst possible outcome, also resulting in stress. Consistent with this idea, research has shown a general pattern of positive effects on wellbeing as a function of increased choice. For example, a study on healthcare outcomes looked at the impact of DC on patients' satisfaction with the care they received before and after surgery and on patients' adherence to treatment recommendations made by surgeons (Ghane et al., 2014). Survey results showed that regardless of whether patients explicitly expressed a preference for control in treatment decision-making or not, a greater amount of control was positively related to greater satisfaction with care and adherence to recommendations following treatment. Therefore, it appears that individuals value increased choice in stressing situations, despite the cognitively intense process of weighing several options and deciding which one is best. Before delving into how exactly individuals make these choices, an overview of decision-making is necessary.

Theoretical Foundations of Decision-Making

Decision Theory. Broadly, decision theory focuses on understanding why DM's make the choices they do. There are two overarching purposes of decision theory, which specify two of the three branches of the theory (Grant & Van Zandt, 2008). The first purpose is to describe how individuals actually act, which constitutes descriptive decision theory. The second purpose is to prescribe how individuals should act, which is referred to as prescriptive decision theory. The third branch of decision theory, normative decision theory, assumes a hypothetically perfect way of making decisions in a given situation. That is, taking into account the options available and the environmental conditions at play, a normative model is able to identify the single best choice available to a DM in a particular situation. This identification is typically done through formal mathematical modeling, which provides numerous advantages to be discussed in detail below.

Expected Utility Theory. Examining how individuals should make decisions and how they actually do make decisions has been an important topic, not only in the domain of psychology, but also in the fields of mathematics and economics for decades (Arrow, 1982). One such theory that has come out of these fields is Expected Utility Theory (EUT). Originally proposed by Von Neumann & Morgenstern in 1944 to explain large-scale risk aversion in relation to monetary wealth, EUT asserts that DM's choose between uncertain or risky options by comparing their respective expected utility (EU) values (Von Neumann & Morgenstern, 2004). EU values are the weighted sums of the options available in a multi-options environment, and are calculated by adding the probability of occurrence of each outcome multiplied by its expected value (Mongin, 1997). Since a DM's preferences can be represented by a linear utility function, as indicated by EUT, it is expected that the DM will behave in a way that maximizes his/her EU (Moser, 1990). Therefore, when individuals perform ideally by maximizing their EU, they are following a normative model of decision-making.

Von Neumann Morgenstern Theory. A branch of EUT that deals with choice under risk (which is the primary focus of this research and will be elaborated on more below) is referred to as Von Neumann Morgenstern Theory (VNMT). This theory defines a rational DM as one who conforms to four axioms, or rules: completeness, transitivity, independence, and continuity (Von Neumann & Morgenstern, 2004). Rational choices are generally defined as those that satisfy a set of prescribed requirements, while irrational choices are ones that are inconsistent and/or incoherent in comparison to normative standards (Kahneman & Tversky, 1979). To satisfy the rule of completeness, DM's must have distinct and clearly defined options, allowing them to choose between any of the given alternatives. For example, if option one is winning $10, and option two is losing $2, it is clear that option one is better than option two. The rule of transitivity means that the individual makes decisions consistently. That is, since option one is preferable to option two, the individual is expected to always choose winning $10 over losing $2. The third rule refers to the independent nature of alternative outcomes. This means that the preference for option one over option two holds true always, regardless of whether a third irrelevant option, three, is also available. For example, winning $10 is always preferable to losing $2, even when there is an option that makes it possible to win or lose nothing. Finally, the rule of continuity assumes that if the worst option is combined with the best option, an option in the middle has the capability of being equally enticing. For example, suppose option one is winning $10, option two is winning $8 and option three is losing $2. Winning $10 is clearly better than winning $8, and winning $8 is clearly better than losing $2. However, option two on its own, winning $8, is equivalent to options one and three combined, as winning $10 plus losing $2 equals winning a total of $8. Therefore, a rational DM who follows the four rules prescribed above is expected to conform perfectly to the linear EU function as prescribed by this model. However, perfect performance is not always observed and deviations from the normative model of EUT do occur (Kahneman & Tversky, 1972), which leads to a discussion of the importance of individual differences.

Subjective Expected Utility Theory. As should be clear from the discussion of VNMT, utilities under EUT are viewed as objective. This view does not, however, take into account the possibility of individual differences that may occur in decision-making and in threat appraisal. Even when there appears to be adherence to the four rules of rationality prescribed by VNMT, individual beliefs and appraisals of the options available should be considered. Subjective Expected Utility Theory (SEU) attempts to reconcile this disparity by asserting that different individuals can weight the same utilities differently (Savage, 1954). That is, it is possible for individuals faced with the same threats and probabilities of occurrence to value different options better or worse than their peers. To illustrate this concept, consider any situation in which an individual places bets on a winning item. This could be a horse race or betting on a popular sporting event. Each individual who places a bet in such a case has access to the same knowledge about statistics of past wins/successes, performance of individual players or items, etc. However, it is highly unlikely that every single individual will place his or her bet on the same option. People take known probabilities and expected values into account, but combine this knowledge with their personal beliefs or opinions. In this way, they are applying subjective weights to the utilities (which again are the product of value and probability) they calculate to create believed utilities of each outcome. Even when subjective weights shift beliefs about EU's, individuals will still try to choose the best possible option and thereby maximize the desired outcome of any given multi-option situation. Due to the subjective nature of these utilities, they exemplify individual differences. The modeling of these individual differences is therefore critical to research in the domain of coping with stress and can be effectively captured through the use of formal mathematical modeling.

Formal Models

A formal model refers to any mathematical representation of a system, such that the model representing it is specific, complete, and holds true in all cases. Formally specifying a theory provides numerous advantages (Hintzman, 1991). First, by its definition, a formal theory specifies its own measures, research design, and tests. Second, formal models provide illustrative insights via investigation of the structure of the formulas used to build a theory. Third, formal theories are self-diagnostic, as the specificity and precision inherent in formal theorization allows for identification of what parts of a given theory are weak and/or falsifiable, thereby allowing for improvement of the theory. Fourth, formal theories have a certain degree of aesthetic appeal by providing as much information as possible in the simplest way possible. Finally, there are certain liberating qualities to formal theories, such that there are strict formal rules of logic in place, from which reasoning can then be governed with ease.

For the purposes of this research, a formal model of DC is utilized to investigate decision-making ability within the domain of stress and coping. In relation to this research, formal models are useful for two reasons (Pleskac et al., 2015). First, formal models provide normative standards for behavior. As discussed previously, normative standards in turn form the basis against which actual choice behavior can be compared. Second, formal models provide specific descriptions of real choice behavior carried out by individuals. Both conformity and departure to the normative model expectations can provide a great deal of insight regarding decision-making.

In addition to the formal model aspects of the tested paradigm, this research utilizes a mixture-modeling architecture, which models a mixture of choices in a given situation within a quantitative framework. Mixture modeling provides a way to examine individual differences in coping with stress, through either conformity or departure to the models being tested in an empirical fashion. By specifying the probability of every possible outcome occurring, mixture models provide an empirical benchmark upon which specific responding in the environment can then be compared.

The four components of the model, as in any game-theoretic infrastructure, are: a DM, information about potential outcomes of decisions, actions that can be performed for each decision, and the outcome of each decision (Rasmusen, 2007; Grant, 2016). The model is presented as sets of decision trees, or nested hierarchies, termed architectures. Each architecture is composed of nodes, branches, and leaves (Appendix A). The boxes of the decision tree, referred to as nodes, depict a choice that can be made by the DM. Next, the branches that stem from each node denote an action that can be performed by the DM. Finally, each leaf after an action signifies an outcome, or payoff of the action (Fudenberg & Tirole, 1991; Grant, 2016).

Level of control available to an individual is also not certain, or complete, in every case. That is, choice can be exerted at some levels, or tiers, of a hierarchical decision, and not on others, or even on none of the levels. The three variables used to discuss the amount of control potentially available in the mixture model for the present research are: *C* (complete choice, including information about decisions and decision-making power), *N* (no decision-making power but access to information), and *U* (no information or decision-making power; Grant, 2016). Previous research in the DC literature has developed formulas to calculate the probabilities of achieving the maximum EU (Shanahan & Neufeld, 2010; Shanahan, 2015; see Appendix B), thus providing the normative probability upon which actual individual participant responding can be compared. In order to quantify the findings of the present research, fit of the separate descriptive models (Group and Individualized, to be discussed in detail below) to the normative model expectations will be tested using the likelihood ratio chi-square statistic, G^2 and a Pearson χ^2 value (Grant, 2016). As previous research has tested fit to normative model expectations in a learning paradigm modeling choice under uncertainty (Grant, 2016), a key change in the present research involves manipulation of the learning paradigm to model choice under risk instead. This leads to a discussion of what exactly risk and uncertainty mean and the importance of studying both in relation to DC.

Uncertainty Versus Risk

Considering the notion that judging between utilities relies on either prior experienced or prior provided knowledge (Grant, 2016), it is worthwhile explicating the dichotomy in the literature as it pertains to coping with stress. Prior experienced knowledge represents choice under uncertainty, and studies that employ this type of learning typically manipulate environmental conditions to provide participants with experiences that should lead them to associate certain events with certain probabilities of stress (Luce & Raiffa, 1957). In everyday life, decisions are often made under a degree of uncertainty, particularly when they are made infrequently and individuals have little prior knowledge or feedback from the environment. For example, choosing whether or not to exceed the speed limit in an area an individual has rarely travelled in before would entail uncertainty. While there are generalized known risks (i.e. being pulled over by the police, receiving a ticket, getting into an accident) and generalized known benefits (i.e. arriving to the destination quicker, avoiding a red light) associated with speeding, the probabilities of either a good or bad outcome occurring in this situation are unknown to the driver. The driver must rely on past or present cues from the environment (i.e. whether they see/have seen a speed trap at an upcoming intersection, the relative speed of other vehicles on the road) to determine the probability of a positive or negative outcome occurring.

Prior provided knowledge on the other hand represents choice under risk. In choice under risk, participants are given unequivocal knowledge of the likelihood that each event will lead to an outcome. In the real world, decisions made under risk are typically made often and offer clear information about the advantages/reinforcements and disadvantages/punishments associated with them (Cokely & Kelley, 2009). An example of choice under risk would be deciding which financial investments to make. Individuals looking to invest their money often know of the specific potential benefits and losses from their banker that could occur should the investment thrive or fail. Likewise, lotteries provide the odds of winning and, thus, those choosing to gamble know their odds of winning and are making choices under risk each time they play. With risky situations, it is also important to note that the probability of occurrence cannot be either 0 or 1 (Pleskac et al., 2015). For example, if the probability of winning a lottery was 100% and the individual playing the lottery knew this, this would represent a certain situation, not a risky one, even though both cases involve knowing the probabilities of events.

According to Bayes' theorem of probability theory, prior learned experiences in the environment help individuals assess the probabilities of an outcome occurring in the future when exact outcomes are unknown (Bayes & Price, 1763). Since experiential learning is so significant for choice under uncertainty, it is expected that DM's will update their choices throughout a given decision-making paradigm based on the experiences of stress or threat that they have personally observed. When this uncertainty is eliminated however, this system is less amenable to change. That is, environmental experiences should cause little to no drift in decision-making choices when DM's know the exact probabilities of the outcomes in a given situation.

The extant literature has provided evidence for the existence of several notable differences in decisional choice behavior under risk versus under uncertainty. For example, in one review of the neurological aspects of uncertainty and risk, Cokely and Kelley (2009) originally proposed that different brain regions would be involved for these different types of choice. For example, they predicted that the limbic loop, which is heavily involved in emotion regulation and memory formation, would play a key role for choice under uncertain conditions only. However, their review of the literature found support for involvement of the limbic system for risky choices as well. This research suggested that some neural overlap between uncertainty and risk does exist, but it also found some notable differences. For example, the part of the fronto-striatal loop that mediates cognitive functioning was significantly more involved for choice under risk than uncertainty. Another well-studied difference in the domain of decisional choice pertains to individuals' preferences to engage in risky versus uncertain situations. For example, research has shown that DM's often avoid uncertain outcomes to a greater extent than they avoid risky outcomes, suggesting that uncertainty is perceived as more stressful than risk (FeldmanHall et al., 2016). It has also been shown that individuals who score high on measures of intolerance for uncertainty are more "behaviorally inhibited" in uncertain situations (Dane et al., 2014), whereas no such link has been found in risky situations. Looking more specifically at DC, various studies have similarly examined DC under uncertainty (Morrison et al., 1988; Kukde & Neufeld, 1994; Grant, 2016) and under risk (Kahneman & Tversky, 1979; Shanahan, 2015). However, no such study has examined both uncertainty and risk using the same experimental paradigm to compare responding under both. This leads to a discussion of the contributions of this research to the extant literature and what it hopes to achieve.

The Present Research

There are two aims of the present research. First, it aims to experimentally explore DC under risk using the same novel, formal mixture-model paradigm and population used by Grant (2016) to examine uncertainty. Specifically, differences in model fit, as evidenced by differential responding from predicted probabilities of maximum EU and observed responding, between three separate models will be examined. Following Grant (2016), the three models of interest are a Conditional model (e.g. the objective probabilities of each event occurring, based on environmental conditions), an Individualized model (e.g. each individual's subjective probability ratings), and a Group model (e.g. the group average of individual subjective probability ratings). The use of individualized SEU performed the best under uncertainty, however it is hypothesized that findings between the three models should not deviate as much under risk, given that all individuals will have access to the same knowledge about the probabilities of stressor occurrence. The choices, actions, and outcomes involved in the risky paradigm are specifically and completely defined, such that individuals know exactly what is expected of them and what will lead to the best possible outcome in any scenario. Assuming that individuals learn the rules and probabilities perfectly, individual subjective values should align fairly well with the objective probabilities prescribed by the normative model. Given the importance of individual differences and subjectivity as discussed previously however, some deviation may still occur.

Second, an examination of individual differences in DC responding will provide further insight into the domain of stress and coping. Such differences will be investigated first through behavioral (i.e. selection of choices throughout the decision-making tasks) and subjective (i.e. probability ratings of the stressors and psychometric profiling) measures (Grant, 2016). Individual differences will also be examined through the collection of psychophysiological measures (i.e. skin conductance and heart rate monitoring). However, these measures will not be analyzed in the present research, but will instead be used in future DC research. Further, an exploratory examination of psychometric measures will also provide insight into whether certain individuals are better than others at exerting DC as predicted by the normative model. Since these psychometric measures were not found to discriminate between individuals on DC amenability when making choices under uncertainty (Grant, 2016), this suggests that the model performed well across participants and no particular psychometric attributes were believe to be responsible for individual differences in DC responding. Thus whether individuals continue to consistently perform well under risk regardless of individual differences is of particular interest.

Overall, understanding both the environment and individual responding within this environment are crucial in enhancing theoretical as well as practical understandings of choice behavior in stressful situations. The present research will allow for a direct comparison between choice under uncertainty and risk, two important aspects in the DC literature. Practically, achieving a cognitively grounded understanding of how and why individuals cope the way they do in certain environments can provide insight into clinical treatment and training programs. This is relevant not only within the domain of psychology but more generally in any situation where person-environment fit is of interest or when individuals are required to make decisions with known probabilities of threat.

Method

Participants

Participants were recruited from Western University's undergraduate research participant pool and received partial course credit for participating. A total of thirty-two participants were tested and six were excluded from final data analysis due to reasons specified in the Results section. Thus, the final sample consisted of 10 males and 16 females (Age $M = 18.8$, $S.D. = 2.11$). Inclusion criteria for the study were that participants had to have good reading comprehension, be right-handed, and younger than 30 years of age. Since most of the instructions and rules for the experiment were written on a computer program, good reading comprehension was required to ensure that participants understood the tasks required of them.

Right-handedness was required to ensure ease of physiological data recording (to be analyzed in the future), as the wires were attached to electrodes on participants' left-hand fingers (to be elaborated on below). Finally, the age restriction was enforced because electrodermal skin activity is known to decrease with age (Grant, 2016; Boucsein, 2012). Individuals were excluded from participating if they possessed hearing impairments, as hearing a white noise is a central component of the study (elaborated on below).

Materials

Cognitive measures. A desktop computer using Windows 7 and equipped with behavioral experiment software called E-Prime 2.0 was used to collect cognitive data. Specifically, a computer paradigm with the rules of the DC framework and a decision-making task was presented to participants. The task involved presenting participants with a decision-making architecture, which looks like a decision tree with two levels, termed the bin level (at the top) and the element level (at the bottom). Each architecture consists of one item in the bin level followed by four branches attached to four elements underneath. Two architectures were presented on the screen at one time, and individuals were asked to make the best possible selection. That is, the selection with the lowest probability of stressor occurrence. Various levels of information and control were provided within the various architectures. At each of the element and bin levels, individuals either had full choice, no choice, or an uncertain choice, referred to as C, N, and U respectively. With the various combinations of C, N, and U choices across the two levels, a total of nine architectures were presented throughout the experiment (Appendix C). The specific cognitive data being collected included which letters participants chose on each trial in the testing phase and their reaction time in making these selections. The computer software automatically collected this data.

Psychophysiological measures. Heart rate and electrodermal activity were measured using the MP-150 Data Acquisition System, and ECG-100C and EDA-100C modules. Two adhesive electrodes were placed above the right collarbone and above the left ankle to measure heart rate. An additional two electrodes were placed on the tip of the index and middle fingers on the left hand to measure electrodermal activity. Signals from the electrodes were recorded using a software package downloaded onto a laptop called AcqKnowledge 4.1. Biopac Systems manufactured all of the aforementioned psychophysiological equipment (BIOPAC Systems, Inc., Goleta, CA). Finally, white noise was produced at a controlled level of 85 decibels, and was played through Logitech desktop speakers. This volume was chosen because it is not expected to cause any serious harm to individuals but is loud enough to elicit a physiological response.

Psychometric measures. A survey was administered on a laptop using Qualtrics™ software and was composed of sections taken from six published measures examining various dispositional and personality traits of individuals, which are believed to influence DC responding. This survey was previously used by Grant (2016) to examine individual differences in choice under uncertainty. Therefore, using the same measures in the current research will allow for a direct comparison of individual differences in DC responding for choice under risk versus uncertainty. The specific measures used in the survey include the Desirability of Control Scale (DOC; Burger & Cooper, 1979), the Need for Cognition Scale (NFC; Cacioppo et al., 1984; Cacioppo & Petty, 1982), the Intolerance of Uncertainty Scale (IUS; Freeston et al., 1994), the Uncertainty Tolerance Scale (UTS; Dalbert, 1996, 1999), the General Decision-Making Style Questionnaire (GDMS; Scott & Bruce, 1995), and the Trait Scale of the Endler Multidimensional Anxiety Scale (EMAS-T; Endler et al., 1991). The DOC, NFC, IUS, GDMS, and EMAS-T have all also been used effectively in previous DC research conducted by

Shanahan (2015), and the UTS has been used successfully in various other studies (Dalbert, 1999; Bude & Lantermann, 2006).

Desirability of Control. The DOC is composed of 20 items using a 7-point Likert scale, ranging from 1 (*The statement does not apply to me at all*) to 7 (*The statement always applies to me*). High scores indicate a high motivation to have control over events in an individual's life and low scores indicate low motivation for control. Sample items from the DOC include "I prefer a job where I have a lot of control over what I do and when I do it" and "I try to avoid situations where someone else tells me what to do."

Need for Cognition. The NFC consists of 34 items measured on a 9-point Likert scale, ranging from -4 (*Very strong disagreement*) to 4 (*Very strong agreement*). High scores indicate an inclination to use information processing and an enjoyment in doing so, while low scores indicate a lack of desire to process information and engage in cognitive tasks. Some of the items on the NFC are reverse-scored, in which case high scores indicate that an individual does not enjoy activities involving information processing. Sample items from the NFC are "I am not satisfied unless I am thinking" and "Simply knowing the answer rather than understanding the reasons for the answer to a problem is fine with me" (reverse scored).

Intolerance of Uncertainty. The IUS is composed of 27 items using a 5-point Likert scale, ranging from 1 (*Not at all characteristic of me*) to 5 (*Entirely characteristic of me*). High scores on this measure indicate poor tolerance of uncertain situations while low scores indicate good tolerance of uncertainty. Sample items from the IUS include "When I am uncertain, I can't go forward" and "The smallest doubt can stop me from acting." The IUS is scored using a single summary score, but recent research has identified two underlying factors that are prevalent in the IUS. Specifically, Birrell et al. (2011) defined the first factor as the "desire for predictability and an active engagement in seeking certainty" and the second factor as the "paralysis of cognition and action in the face of uncertainty." Thus in our analyses, individuals will receive a score for IUSTotal, IUSFactor1 and IUSFactor2.

Uncertainty Tolerance Scale. The UTS is an eight-item scale measured on a 6-point Likert scale from 1 (*Strongly agree*) to 6 (*Strongly disagree*). High scores represent low tolerance towards uncertainty, while low scores indicate a high tolerance for uncertain situations. Sample items from the UTS include "I like unexpected surprises" and "I like to know what to expect" (reverse coded).

General Decision-Making Style. The GDMS consists of 25 items and is broken down into five scales: Rational, Intuitive, Dependent, Spontaneous, and Avoidant. Each scale consists of five questions rated on a five-point Likert scale, ranging from 1 (*Strongly disagree*) to 5 (*Strongly agree*). A sample item from the Rational scale is "I double-check my information sources to be sure I have the right facts before making decisions." A sample item from the Intuitive scale is "When I make decisions, I tend to rely on my intuition." A sample item from the Dependent scale is "I use the advice of other people in making my important decisions." A sample item from the Avoidant scale is "I often procrastinate when it comes to making important decisions." Finally, a sample item from the Spontaneous scale is "I often make decisions on the spur of the moment." The version of the GDMS used in the present study is missing one of the original items published in the Rational scale, but this modified 24-item scale has previously been used successfully for psychometrical profiling (Grant, 2016; Shanahan, 2015).

Endler Multidimensional Anxiety Scale- Trait scale. The EMAS-T measures trait anxiety across four dimensions: physical danger, social evaluation, novel situations, and daily routine. For each dimension a situation is presented, along with 15 statements pertaining to an individual's emotions and responses. For example, the situation for social evaluation states, "You are in situations where you are being evaluated by other people. We are primarily interested in your reactions in general to those situations where you are being evaluated or observed by other people. This includes situations at work, at school, in sports, in social situations, etc., where people might be observing, grading, or judging you." Sample statements relating to the situations include "seek experiences like this" and "feel comfortable" and are measured on a five-point Likert scale, ranging from 1 (*Not at all*) to 5 (*Very much*).

Subjective measures. Participants' self-reported subjective behavior was measured using the probability rating and rank ordering sheets created by Grant (2016).

Probability-rating sheet. Participants were asked to denote the approximate probability with which they believed each letter is associated with a stressor following the practice phase and each of the three subsequent testing phases of the experiment. The letters were scrambled on each sheet and were never presented in the same order as participants originally learned in the learning phase of the experiment. See Appendix D for a sample probability-rating sheet.

Rank-ordering sheet. Participants were also asked to rank each of the letters from lowest to highest probability of being paired with a stressor. The letters were again scrambled and 10 blank spaces were provided for participants to fill in their ordering. The rank-ordering sheet was administered along with the probability-rating sheet following the practice phase and all three testing phases. See Appendix E for a sample rank-ordering sheet.

Procedure

Participants were tested individually in room's 6A and 6B of Westminster Hall, which are adjacent and separated by a two-way mirror to allow the research assistant to observe participant responding throughout the experiment. Room 6A was equipped with a laptop, which was used to administer the survey in the first phase of the experiment and to record the electrophysiological responses throughout the last phase. Room 6B contained the desktop computer on which the DC paradigm was presented for the second, third, and fourth phases. Following the same procedure employed by Grant (2016), testing took place in four phases: measures, learning, practice, and testing.

Participants were first provided with a letter of information (Appendix F) and were played a one-second sound clip of the stressor to be used in the testing phase of the study. Upon approving the noise, individuals were asked to provide informed consent (Appendix G). Once informed consent was obtained, the measures phase began and participants were seated in room 6A in front of a laptop. They were asked to complete a digital questionnaire, composed of questions from each of the six scales discussed earlier. The duration of this first phase was approximately 20 minutes.

Next, participants were led to room 6B to begin the learning phase. Here they were seated at a table with a desktop computer and were presented with 10 letters and their corresponding probabilities of being paired with a stressor (Appendix H). In order to successfully complete the learning phase, participants were required to match the letters with their correct probabilities twice consecutively without any errors. This phase took approximately 15 minutes to complete. Once participants were done, they were asked to ring a bill on the desk indicating to the research assistant they had completed the learning phase.

Prior to beginning the practice phase, the research assistant attached the electrodes to the participant in order to allow sufficient time for the electrodes to calibrate and adhere to the skin. The practice phase was used to provide participants with the rules of the DC framework and allow them to practice making decisions exactly as they would later be expected to in the testing phase. For this phase, participants were given a sheet of paper that contained 10 new letters with new probabilities of being paired with a stressor. They were asked to make decisions in the practice phase using these new letters but were also told that the 10 original letters and their probabilities would be used in the final phase of the experiment. The stressor (white noise) was not presented during the practice phase, but feedback was instead provided on the computer screen following each decision made by the participant. The duration of the practice phase was approximately 15 minutes. Upon completion of this phase participants were again prompted to ring the bell. The research assistant came into the room to attach the wires to the previously adhered electrodes to begin electrophysiological recording of the participant's responses during the final phase of the experiment. Participants were also asked to fill out the first set of probability-rating and rank-ordering sheets at this time.

The testing phase included the same stimulus presentation as the practice phase. Participants were expected to be familiar with the rules and comfortable with the DC paradigm by this point and were asked to respond as promptly and accurately as they could while using the letters they originally learned. The testing phase was broken down into three blocks, and all nine architectures discussed previously were presented 12 times within each block. Each block took approximately 30 minutes to complete. Before each decision-making architecture was presented, a blank screen with "relax" written on it was presented for three seconds so as to allow physiological responding to reach baseline. Participants were then asked to press and hold the space bar, which would present the architecture. When participants were ready to make their decision, they were expected to release the space bar and type the chosen letter on the keyboard. Holding the spacebar thereby acted as a reaction-time measure of decision-making in this experiment. Two seconds after making their selection, participants were either exposed to a stressor or an innocuous event (green screen) for one second, which is believed to be sufficient time to induce a physiological response.

Good performance reduced the probability of stressor occurrence, but it was not eliminated completely even if an individual were to perform perfectly. This is due to the fact that even the best letters had a small probability of being paired with a stressor. Half a second following the innocuous event or stressor presentation, the next “relax” screen was presented and the task was repeated. A stress measurement scale was also administered on the screen after four presentations of decision-making architectures. Participants were asked to indicate how much stress they were experiencing on a scale ranging from 1 (*No stress*) to 5 (*A lot of stress*). At the end of each block in the testing phase, participants were asked to complete a probability-rating and rank-ordering sheet. Repeated administrations of these subjective measures ensured ongoing monitoring of individuals’ beliefs throughout the experiment. After the final block and completion of the sheets, participants were debriefed (Appendix I), thanked for their participation, and dismissed. The total duration of the study was approximately two and a half hours, and participants were assigned four course credits for full completion, or .5 credits per half hour completed if they chose to stop earlier.

Results

Data Cleaning Procedures

Prior to analysis, data cleaning procedures employed by Grant (2016) were implemented to remove participants whose significant inconsistent responding to the learned letters throughout the testing phase of the experiment indicated learning had not been retained or potential random responding had occurred. First, participants’ rank ordering and probability judgment responses were compared across four trials (following the learning phase and then again after each of the three blocks of the testing phase). Final scores for each individual consisted of their average responding across all four instances, since this was not expected to differ significantly throughout the experiment. Calculations of Spearman's rank correlations were then performed and scores with correlation coefficients below .60 served as an indicator of poor learning. For example, if an individual ordered the letters completely differently across all four instances, this would result in a low correlation. On the other hand, if individuals ranked the letters the same each time, as they should if perfect learning occurred, all four trials would be perfectly correlated with each other, resulting in a correlation of 1. Only participants who achieved a Spearman's rank correlation above .60, which suggests a strong or very strong correlation (Grant, 2016; Evans, 1996) were included for the next round of analyses. This procedure removed two participants from the sample, leaving 30 individuals for further analysis.

Secondly, participants' actual selections on the computer paradigm were considered in order to remove any individuals who failed to follow the rules of the DC framework consistently. For example, consider a condition in which the individual has full choice and the letter J (which has the lowest probability out of all 10 letters) is not available for selection. An individual who selects the letter J in this case would be viewed as not following the rules, as the letter was not selectable in the presented case. All three blocks of the testing phase were taken into consideration and participants who were observed to have inconsistent rule following more than 10% of the time were also removed from the final sample. In some cases data could also be recoded. For example, in a situation where an individual was forced to make a certain choice (i.e. they had no information or control at either levels of the decision-making architecture), the correct answer could be inferred and was recoded. If recoding reduced the amount of inconsistent responses to below 10%, these individuals were included in the final sample. This procedure removed an additional four participants, leaving a final sample size of 26 participants. A priori power calculations indicated 26 as a minimally appropriate sample size needed to achieve statistical power of 0.99 (Cohen, 1998).

Testing Model Fit

As previously discussed, three models were slated to explore fit with the normative model expectations: Conditional (i.e. objective probabilities of stressor occurrence), Individualized (subjective ratings of stressor occurrence), and Group (group average of subjective ratings). In order to arrive at an individual value for each participant, probability ratings were averaged across all four trials (following the learning phase and after each of the three blocks of the testing phase) just as they were when calculating Spearman's rank in the data cleaning procedures discussed above. In cases when one or more letters were tied in rank for a given participant, their rank orderings were compared across all four trials and averaged ranks were used to break the tie. For example, consider that the letter M has an objective probability of 0.22 of being paired with a stressor while the letter B has an objective probability of 0.33. When ranking the probability of each letter being paired with a stressor an individual should therefore rank M as lower than B every time. However, suppose a given individual marked M as having a lower probability than B on two out of four trials and higher on the remaining two. Further, imagine that this caused M and B to be tied in probability for being paired with a stressor. In order to break the tie, this individual's rank orderings on all four trials would be considered individually. If this individual consistently ranked M as being better than B on their rank ordering sheets, their rank ordering would break the tie and M would be considered lower than B. In order to arrive at the group value, a group mean of all the individual means was calculated. While Grant's (2016) study on choice under uncertainty found differences between each of the three models, in this study under risk, the Group model values perfectly aligned with those of the Conditional model. This indicates that the group average rank ordering of the letters were the same as the true ranks of the conditional group. Thus, for the purposes of our analyses, only two models, Conditional and Individualized, will be considered for subsequent analyses.

G^2 and Pearson χ^2 Calculations

The likelihood ratio chi-square statistic, G^2 and a Pearson χ^2 value were used to examine model fit of the Conditional and Individualized models to participant responding. These model-fit indices test individual responding in relation to the models' predictions and examine how much of these responses are due to chance. Unstandardized residuals for the G^2 and χ^2 values were examined to test the assumption of normality. For G^2, $D(26) = .20$, $p = .007$ and $W(26) = .80$, $p < .001$ for the Conditional model and $D(26) = .24$, $p = .001$ and $W(26) = .76$, $p < .001$ for the Individualized model. For Pearson χ^2, $D(26) = .27$, $p < .001$ and $W(26) = .66$, $p < .001$ for the Conditional model and $D(26) = .29$, $p < .001$ and $W(26) = .62$, $p < .001$ for the Individualized model.

A log10 transformation was conducted to address the presence of violations in normality in the data (Grant, 2016; Field, 2013). This transformation resulted in no significant violations in normality and that removal of outliers was unnecessary. Given that the results from our analyses matched the results achieved through the log10 transformation, the following calculations of the analysis of variance and correlation analysis were conducted with the untransformed data.

Repeated measures mixed-design ANOVA

A mixed-design analysis of variance was used to contrast the impact of model type, Conditional and Individualized, on individual responding in order to determine if any significant differences exist between the means of the two models. Although two groups were tested (G^2 and

χ^2), a mixed-design rather than a repeated measures design was implemented as an interaction effect was not being examined. Rather, this was done to control for the alpha level, making sure this value was not inflated. The Group model was not considered in this analysis because the Group and Conditional values were observed to align, as mentioned previously. Therefore to allow for simplification and avoid redundancy, only the Individualized and Conditional models were compared. Results showed that the omnibus ANOVA F-test was not significant for both G^2, $F(1.00, 25.00) = 77.60$, $p = .729$, $\eta_p^2 = .005$ and χ^2 values, $F(1.00, 25.00) = 4204.58$, $p = .528$, $\eta_p^2 = .016$.

A priori post hoc tests were conducted using the Bonferroni correction. For G^2 values, no significant difference was observed between the Conditional ($M = 103.79$, $SD = 63.57$) and Individualized model ($M = 106.234$, $SD = 71.67$), $p = .122$. Similarly for Pearson χ^2 values, no significant difference was found between the Conditional ($M = 208.95$, $SD = 264.87$) and Individualized model ($M = 190.967$, $SD = 254.97$), $p = .410$. Refer to Figure 1 and Figure 2 for graphs of the estimated marginal means for G^2 and Pearson χ^2 values, respectively.

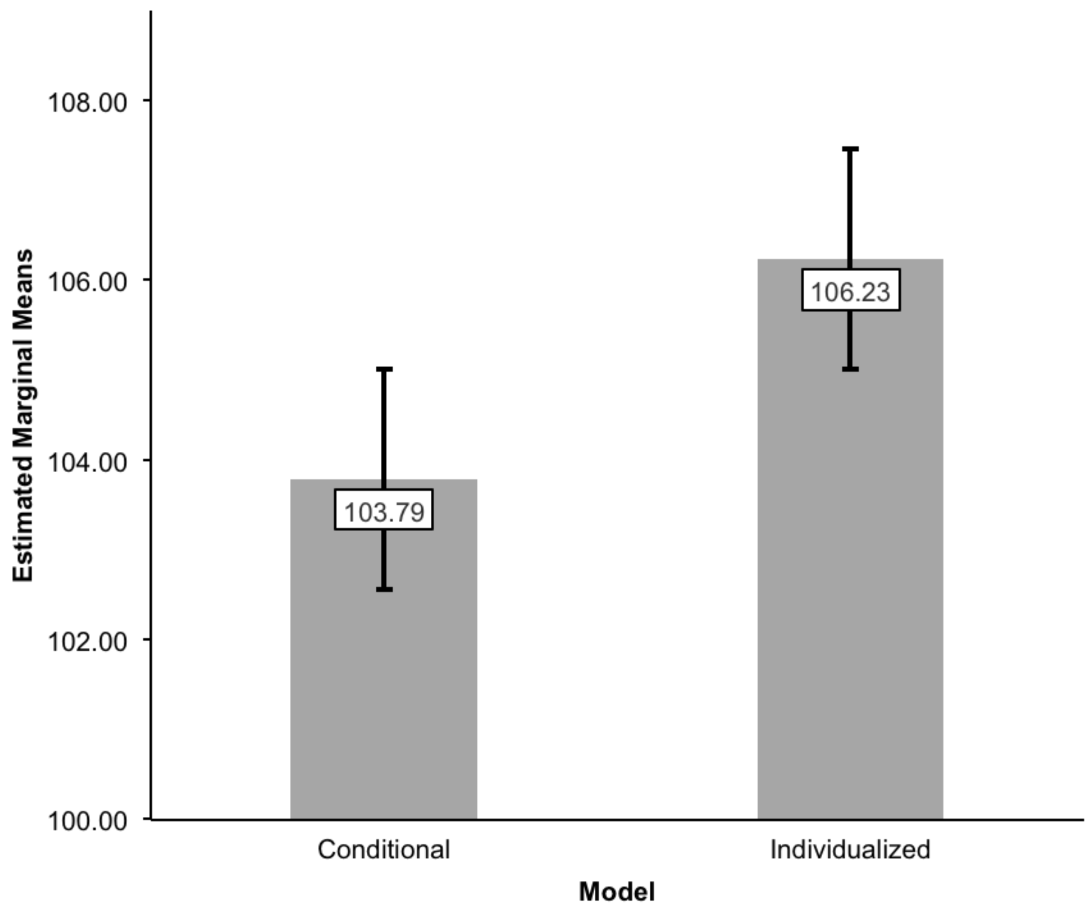


Figure 1. Marginal Means of G^2 values for the Conditional and Individualized models. Error bars represent standard error of the marginal means.

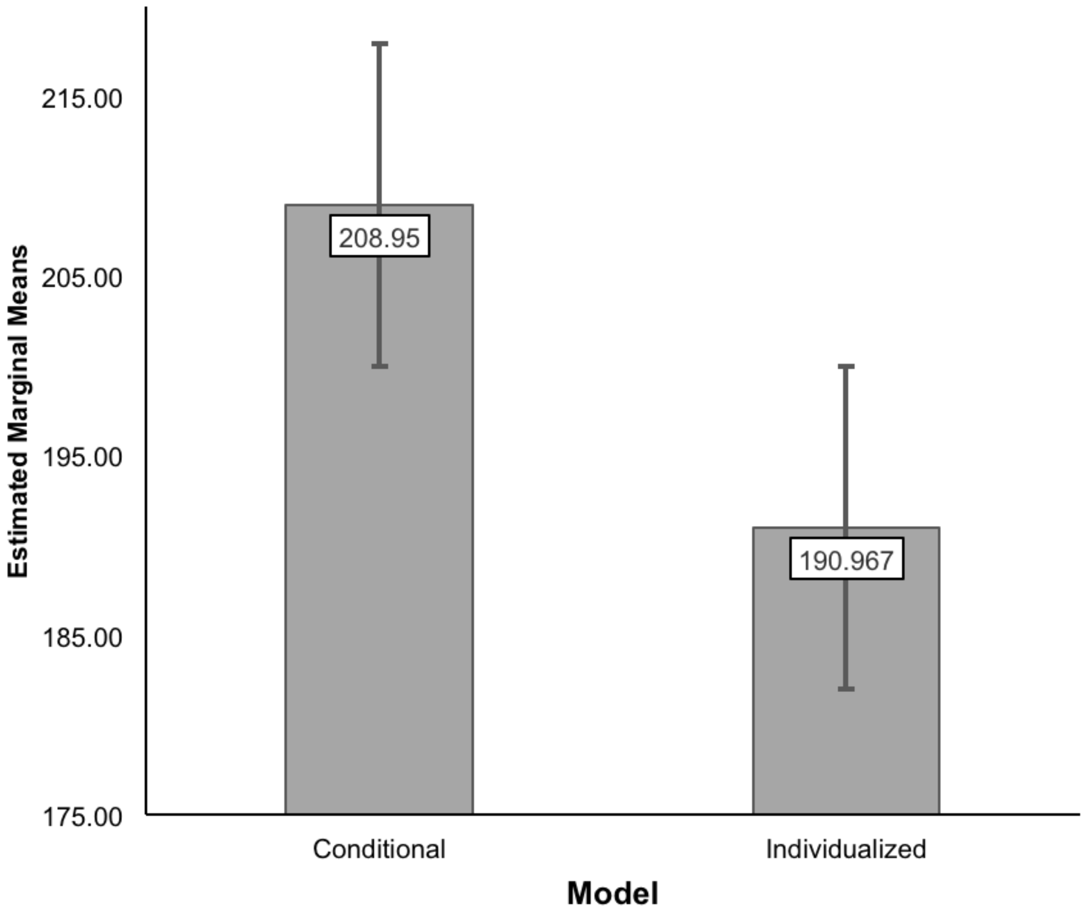


Figure 2. Marginal Means of Pearson χ^2 values for the Conditional and Individualized models. Error bars represent standard error of the marginal means.

Psychometric Correlates

In addition to investigating model fit, the present research also aimed to explore the relationship between various psychometric measures and DC responding. Descriptive statistics of all six psychometric measures examined are reported below. Scores on the DOC were normally distributed (n = 26, M = 99.73, SD = 12.04). Scores on the NFC were normally distributed (n = 26, M = -3.46, SD = 14.93). Scores on the IUS were normally distributed (n = 26, M = 74.12, SD = 18.80), as were the aggregated scores on two additional factors termed IUSFactor1 (n = 26, M = 38.01, SD = 9.95) and IUSFactor2 (n = 26, M = 25.19, SD = 8.20). The UTS was normally distributed (n = 26, M = 28.35, SD = 5.56). The GDMS was normally distributed across all five subscales, including Dependent (n = 26, M = 14.62, SD = 2.37), Avoidant (n = 26, M = 17.77, SD = 1.97), Spontaneous (n = 26, M = 17.96, SD = 2.89), Intuitive (n = 26, M = 10.73, SD = 3.19), and Rational (n = 26, M = 16.04, SD = 2.93). Finally, the Trait scale of the EMAS was also normally distributed across all four dimensions, including Physical Danger (n = 26, M = 46.69, SD = 9.43), Social Evaluation (n = 26, M = 59.73, SD = 8.08), Novel Situations (n = 26, M = 42.54, SD = 11.20), and Daily Routine (n = 26, M = 26.92, SD = 8.13).

A correlation analysis revealed relationships between several psychometric variables that were tested, suggesting the overlap of possible dispositional characteristics in the way individuals approach risky situations. The DOC significantly correlated with the EMAS-PD (r[26] = -.444, p = .023), suggesting that individuals who reported the desire to use cognition are less likely to report trait anxiety towards situations involving physical danger. The DOC also significantly correlated with the EMAS-NS (r[26] = -.546, p = .004), suggesting that individuals who reported the desire to use cognition are also less likely to report trait anxiety towards novel situations. Finally, the DOC significantly correlated with the GDMS-D (r[26] = -.491, p =

.011), suggesting that individuals who reported the desire to use cognition are less likely to approach decision-making with a dependent approach.

All portions of the EMAS significantly correlated with several other psychometric variables. First, the EMAS-NS significantly correlated with both the EMAS-PD ($r[26] = .514$, $p = .007$), and the EMAS-SE ($r[26] = .474$, $p = .014$). This suggests that having trait anxiety in one dimension is often linked to having trait anxiety in other dimensions as well. Specifically, having trait anxiety towards novel situations is linked to also having trait anxiety to situations involving physical danger and social evaluation. The EMAS-NS also significantly correlated with a number of other variables including the IUSTot ($r[26] = .495$, $p = .010$), the IUSF2 ($r[26] = .650$, $p < .001$), the UTS ($r[26] = .448$, $p = .022$), and the GDMS-D ($r[26] = .527$, $p = .006$). Therefore, individuals who express trait anxiety towards novel situations are also likely to be intolerant towards uncertainty, freeze in terms of both action and cognition in the wake of uncertainty, and to endorse an approach to decision-making that depends on others for help. The EMAS-PD significantly correlated with the IUSF2 ($r[26] = .398$, $p = .044$), suggesting those who experience trait anxiety in relation to situations involving physical danger also experience a paralysis of cognition and action when faced with uncertain situations. The EMAS-SE significantly correlated with the UTS ($r[26] = .480$, $p = .022$), suggesting individuals who experience trait anxiety for situations involving social evaluation are less also to evaluate uncertain situations as threatening and/or challenging. Finally, the EMAS-DR significantly correlated with the GDMS-A ($r[26] = -.444$, $p = .023$), which suggests that those who experience trait anxiety in daily routine situations are less likely to endorse an avoidant decision making style.

The three components of the IUS, total, factor 1 and factor 2, were also found to correlate significantly with several other variables tested. First, the IUSTot significantly correlated with the IUSF1 ($r[26] = .912$, $p < .001$), the IUSF2 ($r[26] = .864$, $p < .001$), the UTS ($r[26] = .623$, $p = .001$), and the GDMS-S ($r[26] = .456$, $p = .019$). The strong correlations with the aggregated IUS factors suggests that individuals who have a poor tolerance of uncertainty in general are also likely to desire predictability and actively seek certainty, and to freeze in uncertain situations. The correlation with the UTS and GDMS-S, on the other hand, suggests that individuals with a poor tolerance of uncertainty are also likely to appraise uncertain situations as threatening and are more likely to endorse a spontaneous decision making style. Consistent with these results, the IUSF1 also correlated with the IUSF2 ($r[26] = .603$, $p < .001$) and the UTS ($r[26] = .668$, $p < .001$). Finally, the IUSF2 significantly correlated with the GDMS-D ($r[26] = .529$, $p = .005$) and the GDMS-S ($r[26] = .511$, $p = .008$). This suggests that individuals who fail to think and act in the wake of uncertainty are likely to endorse decision-making styles that are dependent as well as spontaneous.

Finally, various subscales of the GDMS correlated with each other, supporting previous research that suggested that it is not unusual for individuals to assume a combination of the decision-making styles when faced with important decisions (Scott & Bruce, 1995). The GDMS-D significantly correlated with the GDMS-I ($r[26] = .605$, $p = .001$), suggesting individuals who make decisions intuitively are also likely to rely on others to make decisions for them. The GDMS-A significantly correlated with the GDMS-S ($r[26] = .498$, $p = .010$), indicating those who use an avoidant approach to decision-making are also likely to use a spontaneous approach. Lastly, the GDMS-I significantly correlated with the GDMS-R ($r[26] = .795$, $p < .001$), suggesting that individuals who make decisions intuitively are also likely to make decisions rationally.

Correlations were also conducted between fit indexes of the two models, Group and Individualized, to determine whether individual differences as measured through these psychometric variables are differentially related to both of the models. Results showed highly positive significant correlations between Individualized G^2 and Pearson χ^2 values ($r[26] = .941$, $p = < .001$), between Conditional G^2 and Pearson χ^2 values ($r[26] = .953$, $p = < .001$), between Individualized and Conditional G^2 values ($r[26] = .868$, $p = < .001$), and between Individualized and Conditional Pearson χ^2 values ($r[26] = .849$, $p = < .001$). Such strong correlations between the G^2 and Pearson χ^2 values are positive because they indicate that the measures are converging, as they are expected to. The high correlations between the Conditional and Individualized models on the other hand were less expected but also make sense intuitively, as the two models were not found to be significantly different from one another. Finally, none of the model fit indexes correlated significantly with the psychometric variables examined. Refer to Tables 1 and 2 for the bivariate correlations for all psychometric variables and their associations with the G^2 and Pearson χ^2 values.

Table 1

Correlation Matrix for Psychometric Measures and Fit Indices

	DOC	EMAS-PD	EMAS-SE	EMAS-NS	EMAS-DR	IUSTot	IUSF1	IUSF2	NFC	UTS
DOC										
EMAS-PD	-.44									
EMAS-SE	-.28	.33								
EMAS-NS	**-.55**	**.51**	.47							
EMAS-DR	-.19	.21	-.05	.38						
IOUTot	-.03	.35	.35	.50	-.10					
IOUF1	.14	.20	.27	.25	-.14	**.91**				
IOUF2	-.24	.40	.38	**.65**	-.10	**.86**	**.60**			
NFC	-.09	.09	-.05	.26	.07	.48	.39	.45		
UTS	-.14	.29	.48	.45	-.11	**.62**	**.67**	.47	.17	
GDMS-D	-.49	.25	.36	**.53**	.04	.34	.09	**.53**	.11	.26
GDMS-A	.13	-.02	.18	.00	-.44	.28	.29	.15	.07	.27
GDMS-S	.14	.05	.21	.23	-.23	.46	.31	**.51**	.43	.22
GDMS-I	-.34	.14	-.05	.30	.20	-.05	-.23	.07	.21	-.15
GDMS-R	-.25	.24	.01	.36	.22	.07	-.10	.14	.25	-.03
GInd	-.23	-.11	-.16	.27	.18	.10	-.10	.17	.04	-.10
PInd	-.15	-.14	-.08	.26	.16	.06	-.10	.15	-.09	-.05
GCon	-.15	-.05	-.12	.27	.22	.00	-.08	.11	.08	-.09
PCon	-.03	-.08	-.09	.22	.18	.09	.06	.09	.07	-.01

Underline denotes $p < .05$ (2-tailed); Boldface denotes $p < .001$(2-tailed). DOC: Desirability of Control; EMAS: Endler Multidimensional Anxiety Scale – Trait Scale, -PD: Physical Danger, -SE: Social Evaluation, -NS: Novel Situations, -DR: Daily Routines; IUSTot: Intolerance of Uncertainty total score, IUSF1: factor 1, IUSF2: factor 2; NFC: Need for Cognition; UTS: Uncertainty Tolerance Scale; GDMS: General Decision-Making Scale, -D: Dependent, -A: Avoidant, -S: Spontaneous, -I: Intuitive, -R: Rational; GInd: G^2 for Individualized model; PInd: Pearson χ^2 for Individualized model; GCon: G^2 for Conditional model; PCon: Pearson χ^2 for Conditional model.

Table 2

Correlation Matrix for Psychometric Measures and Fit Indices (Continued)

	GDMS-D	GDMS-A	GDMS-S	GDMS-I	GDMS-R	GInd	PInd	GCon	PCon
DOC									
EMAS-PD									
EMAS-SE									
EMAS-NS									
EMAS-DR									
IOUTot									
IOUF1									
IOUF2									
NFC									
UTS									
GDMS-D									
GDMS-A	.08								
GDMS-S	.09	**.50**							
GDMS-I	**.61**	-.07	-.13						
GDMS-R	.45	-.19	.01	**.80**					
GInd	-.12	.02	.24	.12	.12				
PInd	-.15	-.03	.21	.06	.11	**.94**			
GCon	-.14	-.04	.19	.14	.10	**.87**	.12		
PCon	-.19	.04	.19	.12	.13	**.77**	.02	**.95**	

Underline denotes $p < .05$ (2-tailed); Boldface denotes $p < .001$(2-tailed). DOC: Desirability of Control; EMAS: Endler Multidimensional Anxiety Scale – Trait Scale, -PD: Physical Danger, -SE: Social Evaluation, -NS: Novel Situations, -DR: Daily Routines; IUSTot: Intolerance of Uncertainty total score, IUSF1: factor 1, IUSF2: factor 2; NFC: Need for Cognition; UTS: Uncertainty Tolerance Scale; GDMS: General Decision-Making Scale, -D: Dependent, -A: Avoidant, -S: Spontaneous, -I: Intuitive, -R: Rational; GInd: G^2 for Individualized model; PInd: Pearson χ^2 for Individualized model; GCon: G^2 for Conditional model; PCon: Pearson χ^2 for Conditional model.

Discussion

Model Fit Under Risk

The first goal of the present research was to investigate DC responding under risk using the same novel, mathematically specified mixture-model paradigm and population of undergraduate students previously used by Grant (2016) to explore uncertainty. Differential responding between three models were examined in Grant (2016). The first model, the Conditional model, consists of the objective probabilities of stressor occurrence, therefore this model should predict responding if letter probabilities had been learned and selected perfectly according to DC predictions. The second, the Individualized model, concerns each individual participant's subjective probability ratings of stressor occurrence. The third, the Group model, contains the group average of everyone's ratings.

An examination of differences in model fit in the present experiment revealed that the values of the Group and Conditional models aligned, and that these models did not differ significantly from the Individualized model. The fact that the Conditional and Group models aligned under risk is particularly noteworthy. This suggests that on average, the group performed exactly as they were expected to. Therefore, DC predictions from the normative model conform incredibly well to how the group performs on average in risky situations in an experimental setting. Since the Conditional and Group models aligned, the subsequent discussion will refer only to the Conditional model in comparison to the Individualized model for sake of simplicity.

Results also revealed that the Individualized model did not differ significantly from the Conditional model. The fact that the Individualized model did not align with the other two models perfectly points to the influence of individual differences in DC responding. Those individuals who may not have performed as well as the group on average, but did not perform poorly enough to be removed from analysis in the data cleaning procedures discussed previously did impact this model. However, the fact that the difference between the Individualized and Conditional models was not significant again suggests that even when considered individually, participants generally performed well under risk and that the model did a good job accounting for these slight individual differences.

Under uncertainty, Grant (2016) found that the use of the Individualized model provided the best fit for individual responding. That is, there was a significant difference between the models and individuals were found to place more emphasis on subjective expected utilities (SEU) when probabilities of stressor occurrence were unknown. Alternatively, the present results suggest that when probabilities of stressor occurrence are known, either individuals may place less emphasis on SEU's or SEU's and EU's are quite similar. This appears intuitive given that uncertainty, and accordingly the need to subjectively appraise threat, is eliminated in risky situations while it is not in uncertain situations. The fact that all three models predicted fit similarly suggests that individuals generally perform well under risky situations, supporting our hypothesis that the findings between the three models should deviate less under risk than they did under uncertainty.

Given that individuals appear to perform better under risk than uncertainty, this suggests that not only is person-environment fit important but whenever it can, uncertainty should be reduced as much as possible. This would be particularly important in situations requiring high performance. For example, in a work setting, it would make sense to train individuals exactly as they would be required to perform while on the job. Training should aim to eliminate any unknowns by providing employees with clear guidelines and expectations regarding their roles and responsibilities, and training should occur in the same setting that individuals will later be asked to perform in.

Psychometric Correlates

The second goal of the present research was to examine individual differences in DC responding in order to garner further insight into how individuals uniquely cope with stress through an exploratory analysis of psychometric variables believed to influence DC responding. Results revealed that various psychometric variables explored were significantly correlated with each other, but none were correlated with the model fit indexes. In this case, similar results were found for choice under risk as they were for choice under uncertainty (Grant, 2016). Specifically, individuals do not appear to differ on DC amenability as a function of the particular dispositional characteristics explored when making choices under risk. Since individuals generally performed well in this study, these results suggest that people will exert DC well regardless of their individual characteristics.

Despite the lack of significant relationship with the models, various strong and significant correlations were observed among many of the variables examined. For example, various subscales of the EMAS correlated with each other, suggesting that individuals who possess trait anxiety in one dimension are also predisposed to expressing trait anxiety in other dimensions. Similarly, several subscales of the GDMS correlated highly with one another. This suggests that individuals do not often approach decision-making in one singular way but rather integrate different decision-making styles to come to a decision in a given situation.

Several interesting relationships between measures were also apparent. For example, the novel situations subscale of the EMAS significantly correlated with the dependent subscale of the GDMS. This suggests that individuals who express trait anxiety in novel situations also tend to depend on other people to help them make decisions, which is very intuitive. Another example is the relationship between the IUS and the GDMS. The second aggregated factor of the IUS was found to correlate significantly with both the dependent and spontaneous subscales of the GDMS. This suggests that individuals who are paralyzed in terms of cognition and/or action when faced with uncertainty are likely to endorse decision-making styles that are dependent and also spontaneous. While these relationships suggest the overlapping of several important dimensions, it should be noted that the psychometric variables were examined on an exploratory basis only. Therefore, future analyses must be performed to confirm the importance of these and other individual differences on DC responding more specifically, to be elaborated on below.

Limitations and Future Directions

The findings of the present research may be limited by the undergraduate student sample that was used. While this allows for a direct comparison with Grant's (2016) research on choice under uncertainty that also used an undergraduate sample, it is possible that these findings may not hold true for other age groups as well. It is possible that the nature of being a student or being a young person more generally influences how individuals approach uncertain and/or risky situations, in part influencing model fit in both paradigms. For example, the learning styles of individuals who are in an academic setting may differ in important ways from those who are not. In particular, courses in the first year of university are typically very general and often require students to achieve only a surface-level understanding of the subject matter, evaluated through multiple-choice examinations. It is therefore likely that individuals in the sample were apt at memorization, which is critical to success in the DC paradigm used in this study. The fact that individuals performed well under risk may be due in part to their learning style at the time they were tested and other age groups or non-student samples of the same age group may not perform as well. In order to increase generalizability, future research could benefit from comparing choice under uncertainty with choice under risk in samples of other age groups and in non-students to examine whether individualized SEU continue to be more important under uncertainty than risk for all populations and whether other samples continue to perform so well under risk.

Additionally, working memory may be a mediating variable in the present research. It is possible that there is an upper bound limit for working memory for certain individuals in this type of decision-making task. Given that the experimental paradigm is lengthy and involves a learning paradigm, individuals may find it difficult to remember not only the orders of the letters from best to worst, but also their associated probabilities of stressor occurrence. These probabilities are also quite similar for several clusters of letters. For example, the probability is 40% for L, 42% for Z, and 44% for P, which could reasonably lead to confusion and mixing up of ordering. This particular group of letters is especially challenging because the probabilities are not exceptionally high or low, but rather cluster in the middle. Therefore, it may be especially difficult for individuals to accurately remember them perfectly because they are not the best or worst possible options. Finally, some individuals may find 10 letters to be too many to learn and retain throughout the experiment. Feedback from participants suggests that the task places a fair amount of cognitive demand on certain individuals. Therefore, it is possible that individuals with below average working memory performance faired poorer due to their memory rather than their inability to conform to the rules of the DC framework.

The fact that six participants were excluded from the final analysis due to poor rule following and/or learning also limits the results of the present research. It is possible that the individuals who were removed differ in significant ways from those who were not removed, and the psychometric variables measured may have provided unique results in these individuals. It is also possible that some of the individuals who were removed experienced working memory difficulties as discussed earlier. Future research could also explore what makes these individuals different in order to achieve a better understanding of why some individuals exert DC better than others, why some individuals perform better under risk than others, or why some individuals have difficulty with instructions. An understanding of individual differences is particularly important when it comes to the implications of DC because this can help improve person-environment fit, as mentioned previously. For example, consider that future research can show individuals who possess a certain dispositional characteristic, X, are better at performing under risk, while those who possess another characteristic, Y, perform better under uncertainty. We can then work towards matching the X individuals with risky situations and the Y individuals with uncertain situations, whenever possible, to improve performance of both individuals.

Individual differences can also be examined in more depth in future research through an examination of dynamical updating of the DC system. This would provide additional interesting comparisons between the risky and uncertain paradigms. Since the choices, actions, and outcomes involved in the risky paradigm are specifically and completely defined, individuals know exactly what is expected of them and what will lead to the best possible outcome in any scenario. Assuming that individuals learn the rules and probabilities perfectly, minimal drift in decision-making behavior is expected under risk. Uncertainty on the other hand by its definition implies room for error. Since humans are not perfect processors of information and this particular DC task is cognitively demanding, it is reasonable for individuals to drift in their SEU's over time in the uncertain paradigm. As follows from the previous discussion of Bayesian probability learning, it is expected that the DC system will experience less change in the choice under risk paradigm over the three blocks of the testing phase than in the choice under uncertainty paradigm. Since individual responding, in the form of probability judgment and rank ordering sheets, was collected following the practice phase and after each of the three blocks of the testing phase in the present study as well as in Grant's (2016) study on uncertainty, future research could seek to confirm whether less dynamical updating does in fact occur over time under risk.

Finally, individual differences can also be explored further in future research through an examination of electrophysiological data. As elaborated on in the methods section, heart rate and skin conductance of participants was measured throughout the testing phase of the experiment in the present research as well as in Grant's (2016) study. While analysis of this data was beyond the scope of the present research, it can provide fruitful insights into DC responding and should be considered in the future.

Conclusions

Previous research in the domain of stress and coping has examined choice under uncertainty, in which individuals have prior experienced knowledge regarding stressor occurrence, and choice under risk, in which individuals have prior provided knowledge. As no study has directly compared and contrasted responding for both uncertainty and risk using the same experimental paradigm and a similar sample of participants as this experiment has done, this is a major contribution to the extant literature.

A cognitively grounded, sound understanding of how and why individuals behave the way they do in risky and uncertain environments has several practical implications. Specifically, an understanding of the differences in individual responding under uncertainty versus risk is particularly important when considering person-environment fit. The results of the present research suggest that individuals tend to perform better in response to an objective environment under risk than uncertainty. That is, individuals performed the DC task better and their individualized SEU's deviated from the normative model expectations less when uncertainties were eliminated and they had prior provided knowledge of potential stressor occurrence. Therefore, training programs (for employees, in a clinical setting, etc.) may be most effective when they involve giving individuals unequivocal knowledge of what is expected and what the outcomes of a given action are before asking them to perform a given task. Further, training individuals in the same environment they will later be expected to perform in would additionally be beneficial in achieving this person-environment fit.

Given that individuals appear to perform better under risk than uncertainty, elucidating what specifically leads to this differing performance is important. Since none of the exploratory psychometric variables examined revealed significant relationships with the various model fit indexes tested, this suggests the need for further examination of individual differences in DC responding. Such clarification will allow for a thorough understanding of what causes individuals to exert DC the way they do in both risky and uncertain situations.

References

Arrow, K. J. (1982). Risk perception in psychology and economics. *Economic Inquiry, 20,* 1-9

Averill, J. R. (1973). Personal control over aversive stimuli and its relationship to stress. *Psychological Bulletin, 80,* 286-303. doi:10.1037/h0034845

Bayes, M., & Price, M. (1763). An essay towards solving a problem in the doctrine of chances. *Phiolosophical Transactions of the Royal Society of London, 53,* 370-418. doi: 10.1098/ rstl.1763.0053

Benn, K. D. (2002). Formal modeling of decisional-control preferences and mechanisms underlying stress negotiation (Doctoral Dissertation). Retrieved from ProQuest Information & Learning. (AAINQ68027).

Birrell, J., Meares, K., Wilkinson, A., & Freeston, M. (2011). Toward a definition of intolerance of uncertainty: A review of factor analytical studies of the Intolerance of Uncertainty Scale. *Clinical Psychology Review*, *31*(7), 1198-1208.

Boucsein, W. (2012). *Electrodermal activity* (2 ed.). Boston, MA: Springer-Verlag. doi:10.1007/978-1-4614-1126-0

Bude, H. & Lantermann, E.-L. (2006). Soziale Exklusion und Exklusionsempfinden. *Kölner Zeitschrift für Soziologie und Sozialpsychologie, 58*, 233-252.

Burger, J. M., & Cooper, H. M. (1979). The desirability of control. *Motivation and Emotion, 3*, 139-157. doi:10.1007/BF00994052

Cacioppo, J. T., Petty, R. E., & Kao, C. F. (1984). The efficient assessment of need for cognition. *Journal of Personality Assessment, 48*, 306–307

Cacioppo, J. T., Petty, R. E., & Sidera, J. A. (1982). The effects of a salient self-schema on the evaluation of proattitudinal editorials: Top-down versus bottom-up message processing. *Journal of Experimental Social Psychology*, *18*(4), 324-338

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

Cokely, E. T., & Kelley, C. M. (2009). Cognitive abilities and superior decision making under risk: A protocol analysis and process model evaluation. *Judgment and Decision Making, 4,* 20-33

Dalbert, C. (1996a). *Ungewißheitstoleranz und der Umgang mit Ungerechtigkeit.* In C. Dal-bert, Über den Umgang mit Ungerechtigkeit. Eine psychologische Analyse (S. 189-230). Bern: Huber

Dalbert, C. (1996b). *Wie belastbar ist die Ungewißheitstoleranz?* In E. Witruk & G. Friedrich (Hrsg.), Pädagogische Psychologie im Streit um ein neues Selbstverständnis. Bericht über die 5. Tagung der Fachgruppe Pädagogische Psychologie in Leipzig 1995 (S. 676-681). Landau: Verlag für Empirische Pädagogik

Dalbert, C. (1999) Die Ungewißheitstoleranzskala: Skaleneigenschaften und Validierungsbe-funde. *Hallesche Berichte zur Pädagogischen Psychologie* Nr. 1

Dane, J., Kind, A. J., Morrison, A. S., & Heimberg, R. G. (2014). Intolerance of uncertainty and immediate decision-making in high-risk situations. *Journal of Experimental Psychopathology, 5,* 178-190

Dohrenwend, B. S., & Dohrenwend, B. P. (1974). Stressful life events: Their nature and effects. Oxford, England: John Wiley & Sons Inc.

Endler, N. S., Parker, J. D. A., Bagby, R. M., & Cox, B. J. (1991). Multidimensionality of state and trait anxiety: Factor structure of the Endler multidimensional anxiety scales. *Journal of Personality and Social Psychology, 60*(6), 919-926. doi:10.1037/0022-3514.60.6.919

Evans, J. D. (1996). *Straightforward statistics for the behavioral sciences*. Brooks/Cole.

FeldmanHall, O., Glimcher, P., Baker, A. L., & Phelps, E. A. (2016). Emotion and decision-making under uncertainty: arousal predicts gambling during ambiguity but not risk. *Journal of Experimental Psychology: General,* 1255-1262.

Field, A. P. (2013). *Discovering statistics using IBM SPSS statistics: And sex and drugs and rock 'n' roll* (4th ed.). Los Angeles: Sage.

Freeston, M. H., Rheaume, J., Letarte, H., Dugas, M. J., & Ladouceur, R. (1994). *Intolerance of uncertainty scale.* doi:10.1037/t01110-000

Fudenberg, D., & Tirole, J. (1991). *Game theory.* Cambridge, MA; London,: MIT Press

Ghane, A., Huynh, H. P., Andrews, S. E., Legg, A. M., Tabuenca, A., & Sweeny, K. (2014). The relative importance of patients' decisional control preferences and experiences. *Psychyology and Health,* 1105-1118

Grant, B. D. (2016). *Individual differences in stress and coping: testing a model of decisional control* (Masters Dissertation). Retrieved from Electronic Thesis and Dissertation Repository. (4206)

Grant, S., & Van Zandt, T. (2008). Expected utility theory. In P. Anand, P. Pattanaik, C. Puppe (Eds.). *Handbook of Rational and Social Choice*. New York, NY: Oxford University Press

Hintzman, D. L. (1991). Why are formal models useful in psychology? In W. E. Hockley & S. Lewandowsky (Eds.), *Relating Theory and Data: Essays on Human Memory in Honor of Bennet B. Murdock* (pp. 39-56). Hillside, NJ: Lawrence Erlbaum Associates, Inc.

Kahneman, D., & Tversky, A. (1972). Subjective probability: A judgment of representativeness. *Cognitive Psychology, 3,* 430-454

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47,* 263-292, doi: 10.2307/1914185

Kukde, M. P., & Neufeld, R. W. J. (1994). Facial electromyographic measures distinguish covert coping from stress response to stimulus threat. *Personality and Individual Differences, 16,* 211-228

Lees, M.C., & Neufeld, R.W.J. (1999). Decision-theoretic aspects of stress arousal and coping propensity. *Journal of Personality and Social Psychology, 77,* 185-208. doi:10.1037/0022-3514.77.1.185

Luce, R. D., & Raiffa, H. (1957). *Games and decisions: introduction and critical survey.* New York, NY: Wiley

Mongin, P. (1997). Expected utility theory. *Handbook of Economic Methodology* (Eds.), 342-1350.

Moser, P. K. (Ed.). (1990). *Rationality in action: Contemporary approaches*. New York, NY: Cambridge University Press, 11-40

Morrison, M.S., Neufeld, R.W.J., & Lefebvre, L.A. (1988). The economy of probabilistic stress: Interplay of controlling activity and threat reduction. British Journal of Mathematical and Statistical Psychology, 41, 155-177.

Neufeld, R. W. J., Shanahan, M. J., & Nguyen, P. (2014). *Decisional control: A normative model of cognition-intensive coping with stress*. Presented at the Society for Mathematical Psychology, Quebec City, Quebec

Pleskac, T. J., Diederich, A., & Wallsten, T. S. (2015). Models of decision making under risk and uncertainty. In J. T. Townsend & J. R. Busemeyer (Eds.), *The Oxford Handbook of*

Computational and Mathematical Psychology (pp. 209-231). Oxford, UK: Oxford University Press

Rasmusen, E. (2007). *Games and information: An Introduction to game theory* (4th ed.). Malden, MA: Blackwell Pub

Savage, L. J. (1954). *The Foundations of Statistics.* New York, NY: Jon Wiley & Sons, Inc.

Scott, S.G., & Bruce, R.A. (1995). Decision-making style: The development and assessment of a new measure. *Educational and Psychological Measurement*, *55* (*5*), 818-831. doi:10.1177/0013164495055005017

Shanahan, M. J., & Neufeld, R. W. J. (2010). Coping with stress through decisional control: Quantification of negotiating the environment. *British Journal of Mathematical and Statistical Psychology, 575-601*

Shanahan, M. J. (2015). *Mathematical modeling of stress management via decisional control* (Doctoral Dissertation). Retrieved from Electronic Thesis and Dissertation Repository. (3409).

Solomon, S., Holmes, D. S., & McCaul, K. D. (1980). Behavioral control over aversive events: Does control that requires effort reduce anxiety and physiological arousal? *Journal of Personality and Social Psychology, 39,* 729-736

Von Neumann, J., & Morgenstern, O. (2004). Theory of games and economic behavior (60th anniversary ed.). Princeton, NJ: Princeton University Press

Appendix A

Decision Tree

In a given decision tree, the highest level is referred to as the bin level and the lower level is called the element level. In this diagram there are two nodes at the bin level, representing two options that can be made, and four nodes under each bin, representing a total of eight possible outcomes in this particular nested hierarchy.

Appendix B

Formulae for the Probabilities of Engaging Decisional Control structure element i, $\Pr(t_i)$ (Grant, 2016)

$$Pr(t_i)_{CC;\,pq} = \begin{cases} 1.0 & \textbf{if} \quad i = 1 \\ 0 & otherwise \end{cases}.$$

$$Pr(t_i)_{CU;\,pq} = \begin{cases} \dfrac{1}{q} & \textbf{if} \quad i = 1 \\ \dfrac{(q-1)}{q(pq-1)} & \textbf{if} \ i = 2, \ldots, pq \end{cases}.$$

$$Pr(t_i)_{CN;\,pq} = \begin{cases} \dfrac{\binom{pq-i}{p-1}}{\binom{pq}{p}} & \textbf{if} \ i \le p(q-1)+1 \\ 0 & \textbf{if} \ i \le p\,(q-1)+1 \end{cases}.$$

$$Pr(t_i)_{UC;\,pq} = \begin{cases} \dfrac{\binom{pq-i}{q-1}}{\binom{pq}{q}} & \textbf{if} \ i \le q(p-1)+1 \\ 0 & otherwise \end{cases}.$$

$$Pr(t_i)_{UU;\,pq} = \frac{1}{pq}.$$

$$Pr(t_i)_{UN;\,pq} = \frac{1}{pq}.$$

$$Pr(t_i)_{NC;\,pq} = \begin{cases} \dfrac{\binom{pq-i}{q-1}}{\binom{pq}{q}} & \textbf{if} \ i \le q(p-1)+1 \\ 0 & otherwise \end{cases}.$$

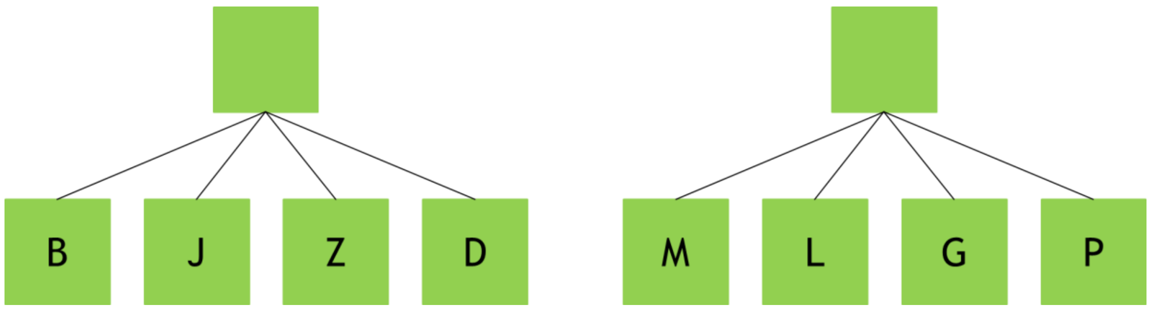
$$Pr(t_i)_{NU;\,pq} = \frac{1}{pq}.$$

$$Pr\left(t_i\right)_{NN;\,pq} = \frac{1}{pq}\ .$$

Appendix C

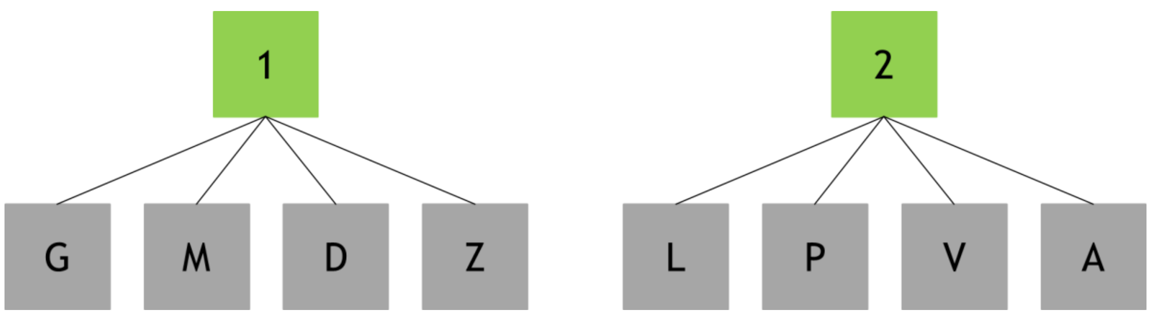
Hierarchal Structures Presented During Testing (Grant, 2016)

CC:



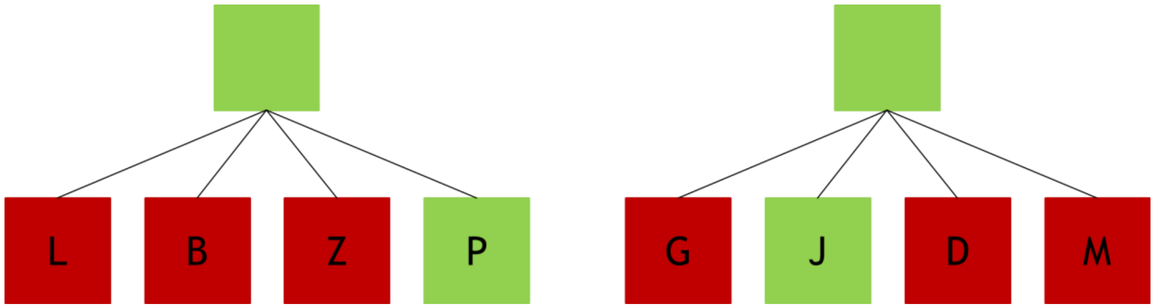
In a CC condition, participants have information and control at both the bin and element level. They can select any letter within either group.

CU:



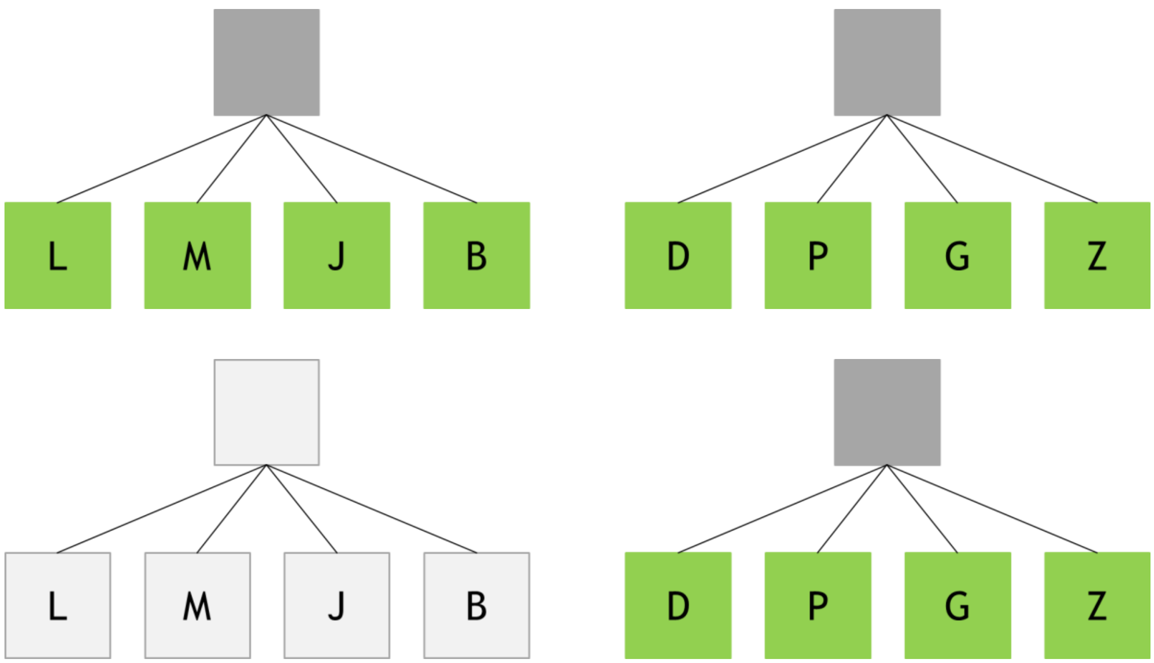
In a CU condition, participants have information and control at the element level, but neither control or information at the bin level. They can select either group (pressing 1 or 2), but a letter at random within that group is assigned to them.

CN:



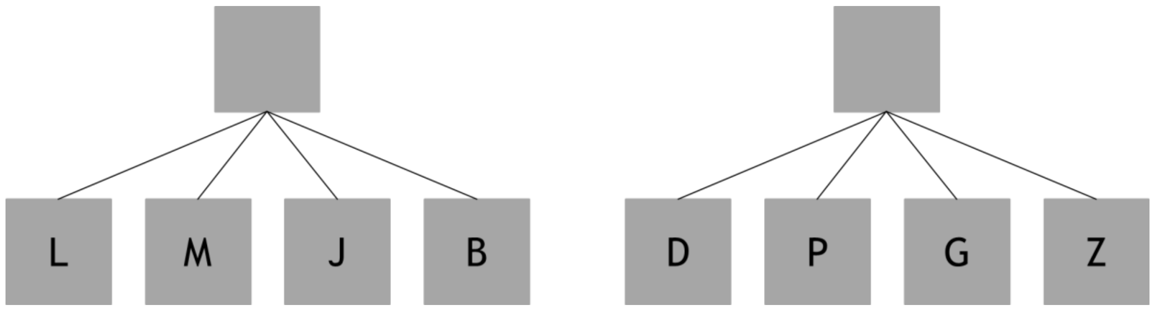
In a CN condition, participants have information and control at the element level, and only information at the bin level. They can only select the letter indicated within each group.

UC:



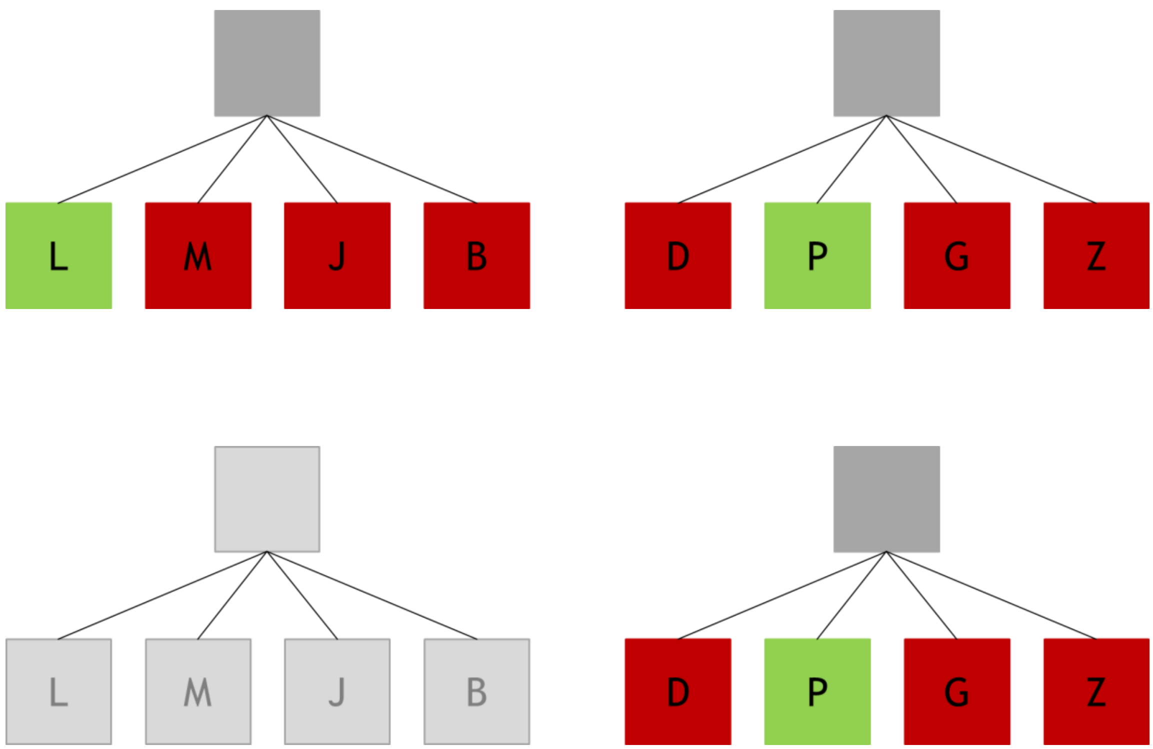
In a UC condition, participants have neither information or control at the bin level, but have information and control at the element level. They can select any letter in either group. Once they have made their selection, the group from which they selected would have its colours fade, indicating that no further selections are available from this group. In the example above, let us assume J was selected in the first group. The participants would then make a letter selection from the other group (P for example) and the letter assigned would be randomly chosen between both letter selections (50-50 chance of either J or P). This is indicative of the participants having either group assigned to them at random, with no information nor control.

UU:



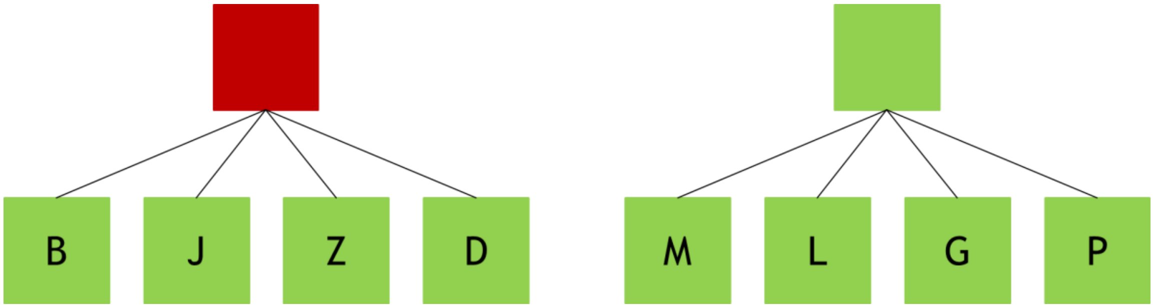
In a UU condition, participants have neither information or control at the bin or element levels. They can select any letter, but are assigned one of the eight randomly.

UN:



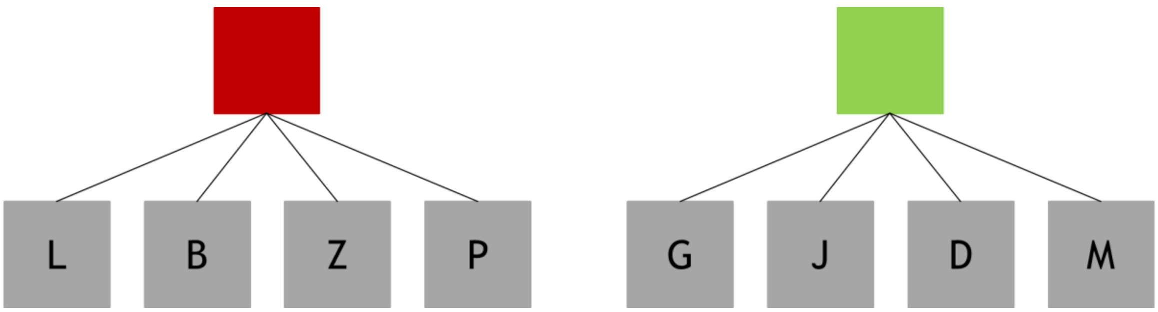
In a UN condition, participants have neither information or control at the bin level and only information at the element level. They can select each letter indicated within each group and are assigned either at random.

NC:



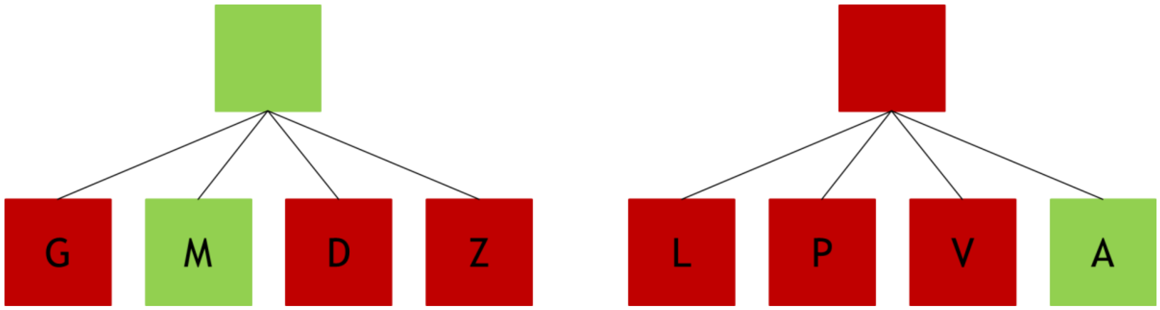
In a NC condition, participants have information, but not control at the bin level and information and control at the element level. They can select any letter within the group indicated as accessible, but are not able to select letters from the other group.

NU:



In a NU condition, participants have only information at the element level and neither information or control at the bin level. They can select any letter within the group indicated, but the letter assigned to them is random within that group.

NN:



In a NN condition, participants have only information at both the element and bin levels. They can only select the letter indicated to them.

Appendix D

Probability Rating Sheet (Grant, 2016)

Probability of a Letter Being Followed by White Noise

Letter

V 0 25 50 75 100

Z 0 25 50 75 100

L 0 25 50 75 100

J 0 25 50 75 100

B 0 25 50 75 100

D 0 25 50 75 100

P 0 25 50 75 100

G 0 25 50 75 100

M 0 25 50 75 100

A 0 25 50 75 100

Appendix E

Rank Ordering Sheet (Grant, 2016)

Probability of a Letter Being Followed by White Noise

Please rank these 10 letters in order from LOWEST to HIGHEST probability of being followed by a noise:

V Z L J B D P G M A

Lowest Highest

___ ___ ___ ___ ___ ___ ___ ___ ___ ___

Appendix F

Letter of Information (Grant, 2016)

Project Title: Individual Differences in Stress and Coping: Testing a Model of Decisional Control
Principal Investigator: Dr. Richard Neufeld, PhD, Psychology, Western University
Co-investigator: Bryan Grant, BSc, Psychology, Western University

Letter of Information

1. **Invitation to Participate**
   You are being asked to take part in a study investigating how people make decisions when faced with stressful situations. Discerning how individuals judge alternatives when faced with a host of aversive events and exert personal control to minimize the anticipated stress can increase our understanding of the cognitive underpinnings of stress.

2. **Purpose of the Letter**
   The purpose of this letter is to provide you with information required for you to make an informed decision regarding participation in this research and stimulate any questions you may have concerning your participation.

3. **Purpose of this Study**
   Stress is a universally experienced phenomenon, but we have yet to understand why stress is generated in response to varying situations. How one assesses stressful situations and the degree to which stress is experienced when control is limited is the target for this study.
   Stress has cognitive, psychophysiological, and behavioural components – thinking about stressful situations and ways of coping, reacting with physical changes (heart rate, sweating, muscle agitation, etc), and choosing what to do – all factor into how stress is experienced and coped with. "Decisional Control" is a method of coping with stress in which the decision maker chooses to insert himself or herself into a stressful situation in order to avoid other situations with higher probabilities of a stressful occurrence. The underlying assumption is that a decision maker, when faced with a selection of varying levels of adverse events, will make judgements (a cognitively-intensive process using learned probabilities) about the stress inherent in each situation and choose available options accordingly. In other words, when an individual is given a choice, he or she will attempt to choose the situation with the least likelihood of producing a bad outcome (with the likelihood being based on previous experience of the bad outcome happening or not). Deciding which situation is the least likely to produce the most stress requires some planning and knowledge about the probabilities that something will go wrong; this, of course, is a thought-intensive process.
   One way of conceptualizing and testing this "decisional control" coping strategy is to use a "game-theoretic approach" whereby stress negotiation is envisioned as playing a "game" with created scenarios. These scenarios combine to form a model (a "game-theoretic infrastructure"), that is used to predict how people are likely to

respond in stressful situations. The model can be thought of as the "board" and the parameters as the "rules". Assuming that people are following the rules and playing using this game-theoretic infrastructure, we are able to predict the advantageous decisions they would make to achieve the best result. One such game-theoretic infrastructure has been created by this lab and simulation work has predicted how people should respond. However, to validate this infrastructure, we need to know if our predictions align with how people actually respond. Thus, the intended purposes of this study are as follows:
1) To compare our generated model's probability predictions to participants' actual behavior, in order to see how well the model predictions accurately describe real responses.
2) To gather data to support this decisional control infrastructure and explore individual differences in responding to stress. These differences may include behavioral (e.g., what people select and the time taken to make these selections), psychophysiological (e.g., heart rate, skin conductance) and subjective measures (e.g., verbal reports about how stressful making selections was through the use of numerical ratings).
By empirically gathering data and modelling behavioral, cognitive and psychophysiological responses to stressful scenarios, we can generate a picture for how people actually do respond. By further incorporating the use of psychometric questionnaires (e.g. personality measures, intelligence tests, preferred methods of coping, etc), individual differences in how decisional control was applied will create a richer picture of how individuals cope with stress. We are also interested in how people in a group respond; by combining all the individual responses, we are able to map out a range of responses that can provide an idea of how a variety of people in a group might respond. In this way, the model will be tested not only at an individual level but also at a group level.

4. **Inclusion Criteria**
Individuals who are under 30 years old, right handed, have no hearing problems and good English reading comprehension are eligible to participate in this study.

5. **Exclusion Criteria**
Non-consenting individuals and those who are 30 years old or older, left handed, having hearing problems or do not have good English reading comprehension are not eligible to participate in this study.

6. **Study Procedures**
This experiment includes a questionnaire phase, a learning phase, a practice phase and a test phase. Before giving consent, you will be briefly exposed to 1 seconds of white noise calibrated to a maximum of 85 decibels (about the noise of a subway car 200 feet away). If you have a hearing impairment or sensitivity, please let the experimenter know, as it is not advisable to continue with the experiment in this case. Prior to giving and documenting written consent, you will hear the 1 second sample of white noise, so that you will know what it sounds like.

In the first phase of the experiment, you will be asked to complete several questionnaires about personality, coping, and decision-making. This should take between 15 and 30 minutes.

For the second phase and third phases, you will be tutored by a set of computer instructions and learning screens and then asked to practice decision-making tasks on the computer (a total of about 45 minutes). During the learning phase, you will learn to associate the probability of a 1 second sample of the white noise, or a green computer screen, for a set of 10 random letters.

Before beginning the next phase, you will receive a brief introduction to the experimental apparatus and fitted by a same-sex research assistant (or choose to apply yourself) with 4 electrodes: one on the neck, one above the ankle, and two on fingers of your left-hand. Depending on the region and in order to attach these electrodes, it may be necessary for you to move or lift the collar of your shirt and/or your pant leg (only during their application and removal of these electrodes). These electrodes are disposable and are only used for one participant and discarded. These electrodes are for detecting a signal and are incapable of delivering a shock.

During the proceeding test phase, the 10 random letters from the learning phase will be presented again for selection in a computer-driven game-theoretic model. These trials presented on the computer will be structures with letters arranged on the bottom that you will have varying amount of control over. You will be asked to consider the layout of these structures and choose a letter available for selection. Upon selection of a letter, you will either experience the white-noise or green-light event based on the probability you learnt in the practice screens. As such, you will experience brief (1 second) instances of the white noise or green light again throughout this phase. In consultation with the Department of Communication Disorders and in keeping with Ontario Ministry of Labor guidelines, this noise exposure is not considered to be harmful in the short duration it will be administered for individuals with normal hearing.

The total amount of time involved for completion of the study is about three to four hours over this 1 session in room 6b of Westminster Hall. You can choose to take part in the entire session or stop at any particular 30 min (approx.) block. Please note that you will be compensated on a pro-rated amount based on how much of the study you complete (see Compensation below). By agreeing to take part in this study, you will be one of a total of 80 participants.

7. **Possible Risks and Harms**

Part of the experiment is to present you with minimal discomfort (i.e., brief exposure to annoying or aversive "white noise”) in order to generate occurrences of varying levels of stress. However, there are no known physical or psychological risks involved and such noise is designed not to harm your hearing. This stimulus is somewhat standard in this type of study and has been used in past studies in this lab.

8. **Possible Benefits**

You may not directly benefit from participating in this study but information gathered may provide benefits to society as a whole by increasing our understanding of individual responding in making choices under stress conditions.

9. **Compensation**
For those in Psych 1000: You will be compensated up to 4 research credits for your participation in this study. If you do not complete the entire study you will still be compensated at a pro-rated amount of 0.5 credit per half hour of participation.
For those in other courses with a research component: You will be compensated according to the criteria set forth on your course syllabus. Please consult your specific course outline for details of your compensation.

10. **Voluntary Participation**
Participation in this study is voluntary. You may refuse to participate, refuse to answer any questions or withdraw from the study at any time with no effect on your future academic status and without loss of promised pro-rated compensation.

11. **Confidentiality**
All data collected, which will be stored by code (and not by name) to protect your privacy, will remain confidential and accessible only to the investigators of this study. The coded data will be stored on a computer hard drive, an external hard drive, and in a locked cabinet all within locked offices. The list of participants' names with their corresponding codes will be stored in a separate locked place. If the results are published, your name will not be used. If you choose to withdraw from this study, your data will be removed and destroyed from our database. All data will be destroyed five years after publication. While we will do our best to protect your information there is no guarantee that we will be able to do so. The inclusion of your initials and your age (years and months) may allow someone to link the data and identify you.

12. **Contacts for Further Information**
If you require any further information regarding this research project or your participation in the study you may contact Dr. Neufeld in Room 310, Westminster Hall, or Bryan Grant, 225 Westminster Hall (ext. 84682, bgrant29@uwo.ca). If you have any questions about your rights as a research participant or the conduct of this study, you may contact The Office of Research Ethics (519) 661-3036, email: ethics@uwo.ca.

13. **Publication**

In publication of results of the study, your name will not be used. If you would like to receive a copy of any potential study results, please provide your name and contact information on the sheet entitled Consent to Contact with Results included in this package.

This letter is yours to keep for future reference.

Appendix G

Consent Form (Grant, 2016)

Consent Form

Project Title: Individual Differences in Stress and Coping: Testing a Model of Decisional Control
Study Investigator's Name: Dr. Richard Neufeld, PhD, Psychology, Western University
I have read the Letter of Information, have had the nature of the study explained to me and I agree to participate. All questions have been answered to my satisfaction.

Participant's Name (please print): ______________________________

Participant's Signature: ______________________________

Date: ______________________________

Person Obtaining Informed Consent (please print): ____________________

Signature: ____________________

Date: ____________________

Letters for Stimulus Presentation (During Learning and Testing Phases) and Associated Probabilities of Stressor Occurrence

Letter stimulus	D	B	J	L	M	A	Z	V	P	G
Conditional probability of stressor	0.71	0.33	0.11	0.40	0.22	0.67	0.42	0.64	0.44	0.69

Appendix I

Debriefing Sheet (Grant, 2016)

Project Title: Individual Differences in Stress and Coping: Testing a Model of Decisional Control
Principal Investigator: Dr. Richard Neufeld, PhD, Psychology, Western University
Co-investigator: Bryan Grant, BSc, Psychology, Western University

Decisional Coping Experimental Debrief Sheet

This study you have just participated in was concerned with how people react when under the effects of stress. Coping with stress is a universal experience and, undoubtedly, one that requires a complex interplay of cognitive functions. Coping with stress can be done in a variety of ways, but choice is key in determining how an individual will respond (Averill, 1973). Through behavioural, cognitive and decisional means, choice in stressful situations offers an advantage of accessing less-threatening alternatives and greater control of reducing stress reactions (Averill, 1973).

Decisional Control is a method of coping with stress in which the decision maker positions “oneself in a stressor situation so as to avoid situational components harboring higher probabilities of stress” (Lees & Neufeld, 1999, p. 185) from a physically or socially adverse event. The underlying assumption is that a decision maker, when faced with a selection of varying levels of adverse events, will make probabilistic judgements (a cognitively-intensive process) about the stress inherent in each situation and make a choice to pursue the option they believe has the lowest associated level of stress.

The paradigm you completed on the computer was one in which decisional control was conceptualized and tested through a game-theoretic approach whereby stress negotiation is cast as playing a game with the environment, the goal of which is to maximize well-being or safety. The stressor used in the experiment was the administration of loud white noise. You were presented with choices involving selection of letters that represented a threat level. Selections varied to some extent in the degree to which they were controllable (i.e., sometimes you were given only one selection and other times you were allowed to make your own choice).

The first aim of this study is to test this game-theoretic infrastructure upon which a mathematical model (technically a probability mixture model) was built. Such an infrastructure (or representative environmental framework) would allow us to develop precise likelihoods of stress-relevant events and test our model at both an individual and group level. If our model predictions align with empirical observations, the model could be adapted for use in future studies with clinical populations with known cognitive and decisional difficulties. This could allow theoretical exploration and interpretation of aberrant or dysfunctional cognition leading to suboptimal, cognition dependant coping strategies in these groups.

In order to quantify and empirically test this environmental framework of decisional control and explore individual differences in responding, behavioural (e.g., choice selection and their latencies), psychophysiological (e.g., heart rate, skin conductance, facial muscle responses) and subjective measures (e.g., verbal reports, numerical ratings) of stress were collected from you. Past research has supported the use of these empirical measures quantifying decisional control composition (reviewed in Shanahan & Neufeld, 2010).

The second aim of this study is to explore how people differ in the way in which they react to similar situations. That is, not all people find controllable situations to be less stressful than uncontrollable situations. In fact, some people may actually find controllable situations to be more stressful than uncontrollable ones. This study was designed to examine the preferences people have about the different kinds of stressful situations they might find themselves in indicative of their decisional coping style. The model will be further augmented with individual-difference psychometric analyses (participants competing personality measures) to explore individual aptitude differences in application of decisional control. The resultant findings will give rise to new model-testing predictions including how individuals use decisional control to varying degrees in making decisions.

If you find you are having trouble managing stress in your own life, or have been upset by anything in particular during this experiment, please let the experimenter know. Two counseling resources available for students include the:

Student Development Centre, Western Student Services Building, Suite 4100, 519-661-3031, www.sdc.uwo.ca

Student Health Services, UCC Rm 11 (basement), 519-661-3030, www.shs.uwo.ca

If you have any questions about the experiment which were not answered during or after the experiment itself, feel free to contact Bryan Grant, Rm 225 Westminster Hall, 519-661-2111 ext. 84682, bgrant29@uwo.ca or Prof. Richard W.J. Neufeld, Rm. 310, Westminster Hall, Phone: 661-3696. If you have questions about your rights as a research participant, you should contact the Director of the Office of Research Ethics at **ethics@uwo.ca**, or 519-661-3036.

Thank you very much for your participation.

References

Lees, M.C., & Neufeld, R.W.J. (1999). Decision-theoretic aspects of stress arousal and coping propensity. *Journal of Personality and Social Psychology*, *77*, 185-208.

Shanahan, M.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*, 575-601.

For further readings, please consult:

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

Levy, L.R., Yao, W., McGuire, M., Vollick, D.N., Jetté, J., Shanahan, M.J., Hay, J. & Neufeld, R.W.J. (2012). Nonlinear bifurcations of psychological stress negotiation: New properties of a formal dynamical model. *Nonlinear Dynamics, Psychology and Life Sciences*, *16*, 429-456.