Cumulative Prospect Theory and Decision Making Under Time Pressure

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Abstract

The current research examined the effect of time pressure on risky decision making. Participants made choices between accepting and rejecting probabilistic gambles under conditions of high time pressure and low time pressure. In order to infer the effect of time pressure on underlying cognitive decision making mechanisms, the data were modeled from a cumulative prospect theory framework (CPT) (Tversky & Kahneman, 1992). It was reasoned that if decisions were guided by the same cognitive processes under low and high time pressure, CPT would adequately describe decision under high time pressure as well as under low time pressure. Two simpler heuristic were suggested as alternative models for decisions under high time pressure. If decisions under high time pressure were based on a different cognitive process, the fit of the CPT model should be poor, and decisions could be adequately - or even better - described by simpler heuristic models that are not subsets of the CPT model. Results showed that time pressure led to substantial changes in how participants integrated values and probabilities in their decisions, with a general tendency to base decisions on the probability of positive outcomes. It was further found that CPT offered a better description for decisions under high time pressure than any of the proposed heuristic models.

Table of Contents

Introduction 1
Risky decision making 1
Cumulative prospect theory 1
Risky decision making and time pressure 4
The present research 6
Methods 8
Participants 8
Experimental design 8
Material 8
Procedure 10
Modelling decision making behavior 12
Cumulative prospect theory 12
Heuristic models 14
Statistical estimation of model parameters 14
Bayesian modelling 15
Results 16
Parameter recovery study 16
Training 19
Experiment 20
Model comparison 26
Discussion 29
CPT and time pressure 29
Shift in decision making process 29
Limitations 30
Conclusions 31

References 32

Appendix A: Table of gamble stimuli 36

Appendix B: Results from training 39

Introduction

Risky decision making

Most decisions must be made without certain knowledge about their outcomes. For instance, decisions such as whether to accept a new job, investing in the stock market or crossing the street all have unpredictable outcomes, that is, they involve components of risk. Besides the many potential applied benefits of understanding such decisions, it is of special interest in psychology to understand cognitive components guiding behavior under risk. Models such as rank dependent expected utility theory (Quiggin, 1992) and cumulative prospect theory (Tversky & Kahneman, 1992) account for decisions under risk by describing a single cognitive process that integrates values and probabilities in an algorithmic fashion. In the last decade, however, a number of experiments have been published that question the generalizability of the value*probability approach (Huber, Beutter, Montoya, & Huber, 2001; Huber & Kunz, 2007; Tyszka & Zaleskiewicz, 2006; Williamson, Ranyard, & Cuthbert, 2000). Theorists such as Gigerenzer have described cognition underlying decision making as a toolbox equipped with different strategies evolved for different problems (Gigerenzer & Goldstein, 1996; Todd & Gigerenzer, 2007). The aim of the current paper is to investigate time pressure as a possible boundary condition, exploring how different decision mechanisms are used under different conditions, and thereby aid understanding of a more general account for how decisions work.

Cumulative prospect theory

The probably most influential theoretical account of risky decision making is cumulative prospect theory (CPT) (Starmer, 2000; Tversky & Fox, 1995; Tversky & Kahneman, 1992; Wu, Zhang, & Abdellaoui, 2005; Wu, Zhang, & Gonzalez, 2004). CPT distinguishes two phases in the decision making process. First, the decision maker constructs a representation of the information relevant to the problem, for instance, identifying the possible outcomes. Second, the decision maker assesses the values of each outcome and chooses accordingly. CPT describes this valuation process by suggesting that people put subjective weights on values and probabilities and that people weight values and probabilities associated with positive outcomes (i.e., gains) differently from those associated with negative outcomes (i.e., losses). Further, CPT assumes that these outcomes are evaluated against a reference point, so that a single outcome is framed in terms of either a gain or a loss, relative to the reference point.

Common methods of studying decision making under risk is to ask participants to choose between monetary options with probabilistic outcomes (Rieskamp & Hoffrage, 2008), choose between monetary options with deterministic and probabilistic outcomes (Busemeyer, 1985; Tversky & Kahneman, 1992), or choose between options of equal expected payoffs but with differing variances (Ben Zur & Breznitz, 1981). For instance, Tversky and Kahneman (1992) asked participants to choose between several options where the outcome of one option was probabilistic whereas the outcome of the other option was deterministic. The probabilistic option, option A, could for example yield 150$ with probability .25 and 25$ with probability .75. The deterministic option, option B, could for example yield 50$ with probability 1. Classic economic theory of decision making would predict that the option with the largest expected value would be preferred (Simon, 1959). The expected value (EV) for an option (O) is given by summing the possible values (x) weighted by their probability of occurring (p):

$$EV(O) = \sum p(x_i)\, x_i \tag{1}$$

The expected value for option A is then:

$$EV(A) = .25 * 150 + .75 * 25 = 56.25 \tag{2}$$

And the expected value for option B is:

$$EV(B) = 1 * 50 = 50 \tag{3}$$

Classic economic theory suggests that the decision maker would maximize the expected value and consequently choose option A over option B, since $EV(A) > EV(B)$. However, Tversky and Kahneman found that people don’t behave as if they try to maximize their expected value; instead they showed that behavior deviates systematically from what would be predicted from classical economic theory. Tversky and Kahneman formulated their findings in terms of risk preferences and suggested that people are risk aversive for gains of high probability but risk seeking for gains of low probability, and people are risk seeking for losses of high probability but risk aversive for losses of low probability. This is known as the fourfold pattern of risk preferences.

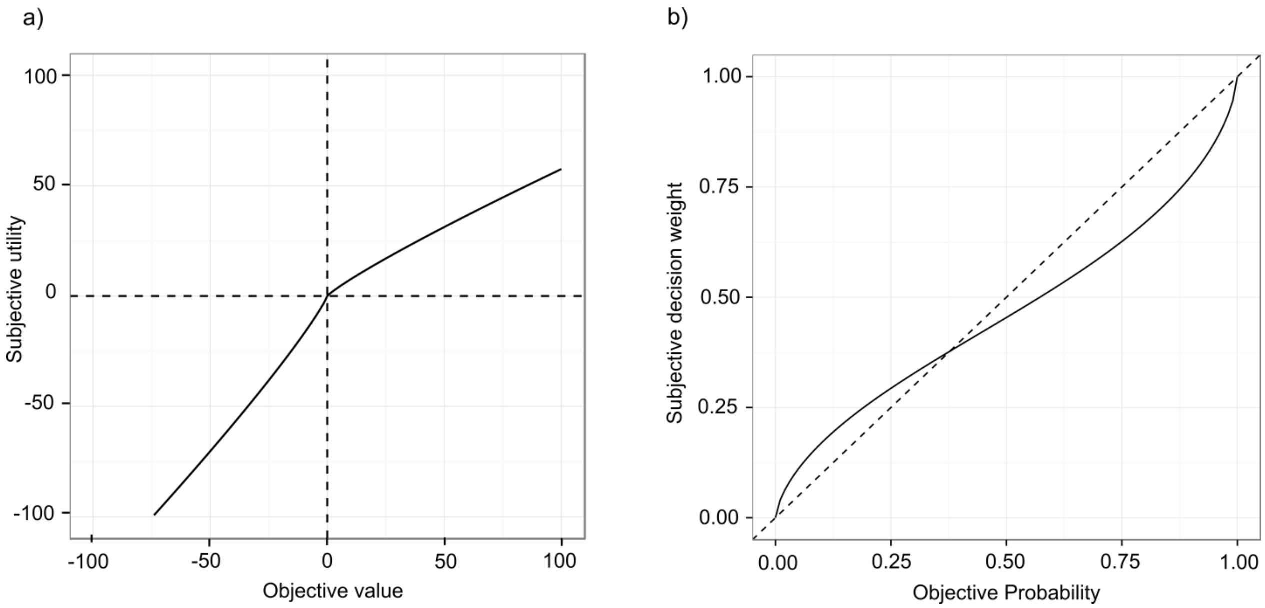

Figure 1. Illustration of weighting functions as described by (Tversky & Kahneman, 1992). (a) The value function for losses is steeper than the value function for gains, making "losses loom larger than gains" (Kahneman & Tversky, 1979, p. 279). (b) The probability weighting function defines how small probabilities are overestimated whereas large probabilities are underestimated.

In contrast to classical economic theory, CPT (Tversky & Kahneman, 1992) predicts these behavioral patterns by describing the functional relationship between objective values and subjective utilities, and the functional relationship between objective probabilities and subjective decision weights. According to CPT, subjective utilities are related to objective values through a sigmoidal function. The relationship between objective losses and subjective losses follows a convex function (see figure 1a), so that negative values are deemed even more negative. On the other hand, the relationship between objective gains and subjective gains follows a concave function (see figure 1a), so that positive values are deemed less positive. In the same manner, objective probabilities are related to subjective decision weights by an inverse sigmoidal function, so that low probabilities are overestimated, whereas large probabilities are underestimated (see figure 1b). According to CPT, the subjective value (SV) of an option (O) is given by:

$$SV(O) = \sum \pi(p_i)v(x_i), \tag{4}$$

Where π is the weighting function for the objective probabilities and v is the utility function for objective values. The weighting function and the utility function are formalized with a set of free parameters defining the form of the functional relationships. For instance, subjective utilities are related to positive objective values by the function:

$$v(x) = x^{\alpha}, \quad (5)$$

Where the parameter α is a constant between 0 and 1. If the parameter α for a hypothetical decision maker were .90, his subjective utility for option A in the gamble presented above would be 90.9$ and 14.8$. Because $150^{.90} = 90.9$, and $20^{.90} = 14.8$. Decision weights are related to probabilities by the function:

$$\pi(p) = \frac{p^{\gamma}}{(p^{\gamma} + [1-p]^{\gamma})^{1/\gamma}}, \quad (6)$$

Where the parameter γ is a constant between 0 and 1. If the parameter γ for the hypothetical decision maker were .70, his decision weights for option A would be .29 and .63 because:

$$\frac{.25^{.70}}{(.25^{.70} + [1-.25]^{.70})^{1/.70}} = .29, \quad (7)$$

And:

$$\frac{.75^{.70}}{(.75^{.70} + [1-.75]^{.70})^{1/.70}} = .63, \quad (8)$$

The subjective value of option A is then:

$$SV(A) = .29 * 90.9 + .63 * 14. = 35.18, \quad (9)$$

Option B involves no components of risk, and therefore remains the same:

$$SV(B) = 1 * 50 = 50, \quad (10)$$

As a result, CPT would predict that option B is preferred over option A, since $SV(A) < SV(B)$. In this example CPT predicts the opposite behavior than expected from a classical economic viewpoint. CPT also aims at describing decisions involving losses and has additional parameters describing weighting functions related to losses. These will be explained in detail below.

Risky decision making and time pressure

Although CPT successfully accounts for a wide range of decisions, its application to decisions made under time pressure has not been thoroughly investigated. Simon (1956) argued that a model of human decision making need to account for limited time, knowledge and computational capacity. Similar arguments have been made by Gigerenzer, suggesting that people change decision strategies depending on their validity for the current problem and situational demands (Todd & Gigerenzer, 2007). These arguments have been supported by several empirical results as well as theoretical models of cognition, suggesting that decisions made under time pressure involves different strategies than decisions made without time constraints. For instance, many experimental studies of task accuracy under time pressure report a speed-accuracy tradeoff (Payne, Bettman, & Luce, 1996; Svenson, Edland, & Slovic, 1990; Zakay, 1993). When the decision maker responds under time pressure, task accuracy decrease compared to decisions made without time constraints. Payne, Bettman, and Luce (1996) suggested that the speed-accuracy tradeoff was a results of a change in decision making strategy, where decisions made under time pressure utilize simpler heuristic processes that rely on only subparts of the available information, thereby producing non-optimal responses. Similar suggestions were made by Rieskamp and Hoffrage (2008). They showed that when constraining time limits to make decisions, either indirectly by imposing costs of being slow, or directly by limiting the time for each decision, a simple heuristic model better predicted people's inferences than a linear model integrating all available information.

Similar predictions are made from the highly influential dual process theories of decision making (Evans, 2008). The core idea underlying these theories is that we possess two cognitive systems of thinking, one fast and intuitive, and one slow and deliberate (Kahneman, 2003; Kahneman & Frederick, 2002). Evans and Stanovich (2013) summarized today's most important accumulated evidence under the dual process framework, and labeled these systems Type 1 and Type 2 processes. They describe Type 1 processes as characterized by being unconscious, rapid, automatic with high capacity, while type 2 processes being conscious, slow, deliberate, and with low capacity. Type 1 processes are assumed to underlie heuristic types of decision making, not capable of producing normatively correct inferences. When summarizing the broad range of research on these systems, Evans and Stanovich (2013) suggests that time pressure is one of the most effective ways of manipulating the decision making process. They propose that by restraining time limits to make decisions, Type 2 process are inhibited due to their slow nature, and only Type 1 processes are capable of producing a response.

The present research

In spite of the large amount of research suggesting that decision making strategies shift as a function of situational demands, in particular time pressure, CPT remains silent about implications of time pressure on decision making processes. In particular, it is unknown if CPT is a good description of risky decision making under time pressure, or if simpler decision mechanisms like heuristics that use less information are better models of the decision making process. The aim of the current paper was to investigate if the same or different decision mechanisms govern risky choices under high time pressure as under low time pressure. CPT is thus accepted as an adequate description of decisions under low time pressure (for criticism of this view see e.g., Birnbaum, 2008; Brandstätter, Gigerenzer, & Hertwig, 2006). It was reasoned that if decisions were guided by the same cognitive processes under low and high time pressure, then CPT should adequately account of decisions under high time pressure. High time pressure could obviously lead to different weighting of information, but this would be captured by changes in parameter values of the CPT model.

However, if decisions under high time pressure were based on a different cognitive process (for example a change from type 2 to type 1 process), decisions under high time pressure could be adequately described by simpler heuristics that use less information and do not integrate probability and value information. For decisions under high time pressure, two simpler, heuristic types of strategies are proposed:

- Decisions are guided by evaluating the probabilities of outcomes to occur, ignoring other information.
- Decisions are guided by evaluating the values of the outcomes, ignoring other information such as their probability of occurrence.

The two simple heuristics were inspired by two simple mechanisms that have previously been used to explain decisions under risk. The heuristic that looks at the values of the outcomes only, were inspired by the minimax rule: choose the option with the highest minimal outcome. The second heuristic that looks only at probabilities was inspired by the suggestion people will choose the option with the lowest probability to lose anything.

These hypotheses were investigated by analyzing data from two separate experiments. In both experiments, the task implied accepting or rejecting probabilistic gambles under conditions of high and low time pressure. The experiments were identical in all respects, except that eye-tracking data were collected simultaneously in one, whereas MR data were recorded simultaneously in the other.

Methods

Participants

A total of 45 participants (23 males and 22 females) participated in the study. Age ranged from 19 to 45 (M = 26.14, SD = 4.36). The complete experimental session consisted of a training session and the main experiment. All participants were tested individually, and experimental sessions lasted for about 45 minutes. All participants were informed about the task and gave written consent. Participants were paid a minimum of 150 NOK for their participation. Additionally, participants received the outcome of 10 trials randomly drawn from the experimental session. Participants were recruited from the University of Oslo and via acquaintances.

Experimental design

A two-alternative forced choice task was used in the two experiments presented in this paper. Data from experiment 1 were collected as part of an eye-tracker study, while data from experiment 2 were collected as part of an MR study. Apart from the different locations of data collection, the two experiments were identical with respect to features of the design. The task involved choosing between accepting and rejecting gambles with probabilistic outcomes. The experimental variables were time pressure (low, high) and advice (advice, no advice). The advice manipulation was related to a hypothesis independent of the current application, but was analyzed here to account for potential influences of advice on decision strategies. Both variables were manipulated within subjects and were fully crossed. The measured dependent variable was choice preferences (dichotomous).

Material

All gambles in the experiment consisted of one gain value with an associated probability, and one loss value with an associated probability. Possible gain values were $[3, 6, 12]$ and possible loss values were $[-3, -6, -12]$. To make the task probabilistic, both values were always paired with a probability from the set $[.2,\ .4,\ .8]$ (see appendix A for all gambles used in the two experiments). All permutations of these four sets of values and probabilities give 81 unique compositions of gambles. Experiment 1 used all of these as gamble stimuli. Experiment 2 used 56 of these gambles as stimuli, selected so that the whole range of expected payoffs was represented (see figure 2).

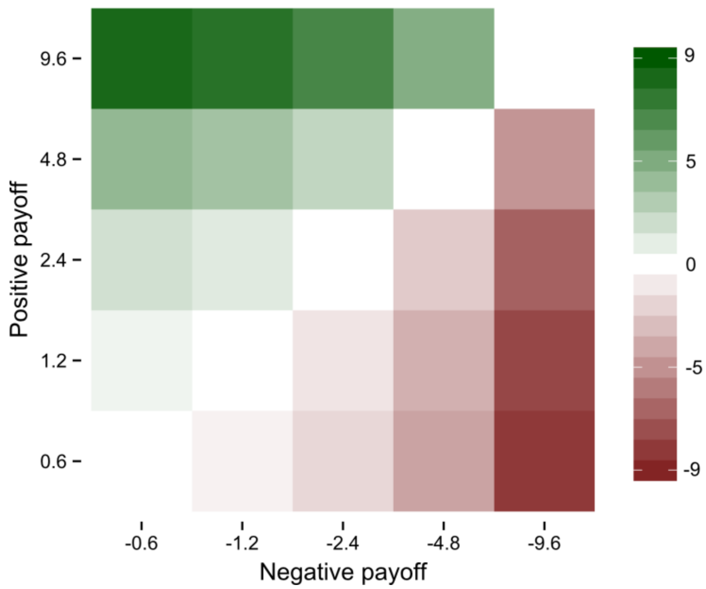

Figure 2. Expected payoffs for all gambles in the experiments. The color matrix represents all possible expected payoffs from the gambles in the two experiments. The expected payoff for a single gamble is: $\sum p(x_i)x_i$, where x_i is one outcome (either positive or negative), and $p(x_i)$ is the probability of that outcome. As illustrated in the figure, the absolute value of all positive and negative payoffs was identical.

During a training session, participants learned to associate the values and probabilities constituting the gambles with different shapes. These shapes were later used to represent the gambles in the main experiment (see figure 3). Each shape represented either: a positive value, the probability of that value, a negative value or the probability of that value. All stimuli shapes were composed of a line with a small circle or rectangle in one endpoint, and a large circle or rectangle in the other endpoint. Determined by counterbalancing across participants, circles and rectangles represented either values or probabilities. The magnitude of both stimuli types (value or probability) was represented by a crossing bar, moving towards the larger endpoint in order to indicate greater magnitudes (either positive or negative). The stimuli shapes were presented either horizontally or vertically in order to represent either gains or losses and their associated probability, also counterbalanced across participants. The value shapes and their associated probability shapes were always presented horizontally next to each other, either at the top of the screen or at the bottom of the screen (counterbalanced across participants). All stimuli were composed of the same pixels, making them identical with respect to luminance and thereby controlling for any perceptual confounds.

Additionally, three stimuli objects composed of circular dots were used to represent advice (see figure 3). Dots arranged as a cross indicated that the gamble should be rejected, dots arranged as a check mark indicated that the gamble should be accepted, and dots arranged as a rectangle indicated that no advice were given. Similar to the gamble stimuli, the advice stimuli were designed to be identical by being composed of the same pixels. The accuracy of the advice cues, were based on observed accuracy levels from a pilot study of the experimental paradigm. Accuracy was operationalized as percentage of choices corresponding to what would be predicted from the expected payoffs of the gambles. Across the two time-pressure conditions, the mean accuracy in the pilot study was about 80%. Based on this, advices in the main experiment were drawn randomly from a Bernoulli distribution with .80 chance of success.

Procedure

The entire experimental procedure was administered via a computer, programmed in Presentation® software (Version 16.3, www.neurobs.com). Prior to the experiment, participants went through a training session in order to reduce potential learning effects during the experimental trials. The training task was identical to the experimental task, except that no experimental manipulations were introduced (i.e., participants had a free time-limit to respond and they were given no advice). In addition, the stimuli were presented against a black background, as opposed to a colored background used in the main experiment to indicate time limits. The training task lasted for 10 minutes and participants were instructed to progress at their own pace. At the beginning of the training session, and after every 20th trial, participants were presented with all experimental stimuli and their associated numeric value, in order to facilitate learning.

After the training session, participants performed the main experiment. Before the experiment started, participants were told that they would be limited to respond within time-limits of 2 seconds or 15 seconds, corresponding to the time pressure manipulation. If no response was given within the time limits, the experiment still progressed to the next trial. Participants were also told that they would receive an advice in half of the trials, based on the behavior of other participants. Additionally, participants were told that they would receive the outcome of 10 randomly drawn trials at the end of the experiment. To make sure participants understood the task, they performed 20 practice trials identical to the experimental trials, before the experiment started.

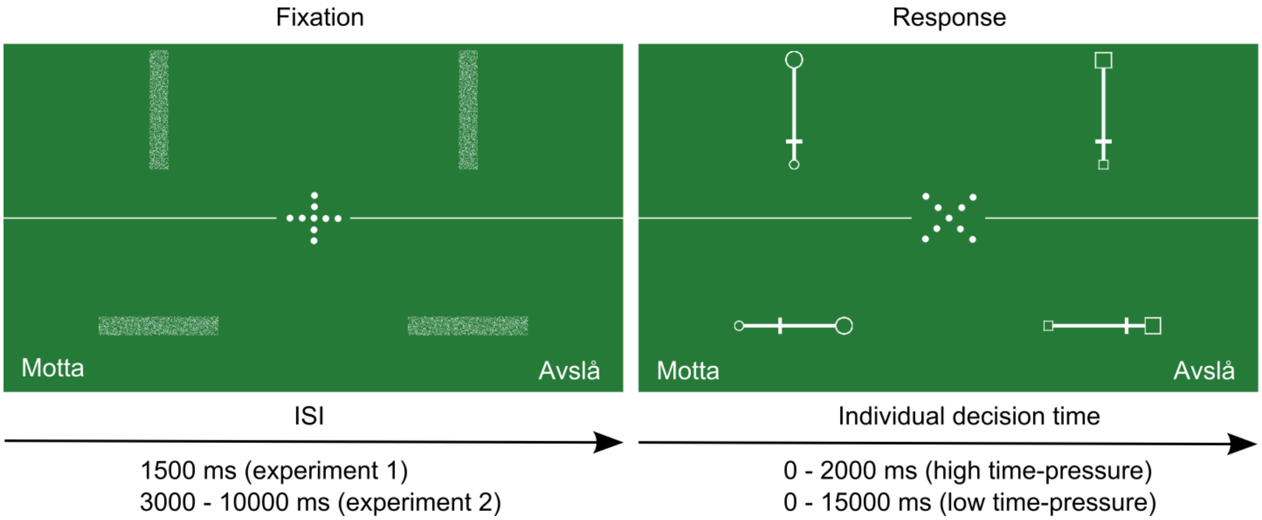

Figure 3. Illustration of experimental paradigm. Between each trial a fixation period (Fixation) were presented for 1.5 seconds in experiment 1, and for random intervals between 3 and 10 seconds in experiment 2. The long inter stimuli interval (ISI) was necessary in the FMRI experiment because trial specific activation was of interest. In the response trials (Response) the stimuli were presented and participants decided to accept or reject the gamble. Under conditions of high time pressure participants had a maximum of 2 seconds to give a response, whereas under conditions of low time pressure participants had a maximum of 15 seconds to give a response. The background color of the stimulus screen (blue or green) indicated whether time pressure was low or high. "Motta" (Norwegian for accept) and "avslå" (Norwegian for reject) were printed in the lower corners, instructing participants which button to press for the desired action.

The two experiments consisted of 324 trials in experiment 1 and 224 trials in experiment 2, distributed across four blocks of 81 and 56 trials, respectively. The presentation sequence of the gambles were randomized within the four experimental conditions, with the constraint that the same gambles were presented under all conditions, making sure no bias was introduced between conditions by properties of the gambles. Time pressure was manipulated block wise so that a single block contained only trials of high time pressure or low time pressure. Block-sequence was counterbalanced across individuals with the constraint that conditions always were interspersed. Average duration of low time-pressure blocks were 6.5 minutes (SD = 1.6), while average duration of high time-pressure blocks were 4.8 minutes (SD = 1.4). At the beginning of each block, a screen informed the participants whether the time limit to respond for the following block of trials was 2 seconds or 15 seconds. Advice was manipulated within each block, in series of four trials of advice or no advice.

Modelling decision making behavior

In order to investigate the effect of time pressure on decision making, the approach of the current paper was to explicitly formalize the hypothesized processes as statistical models. The approach is advantageous because it allow quantification of aspects of the decision making process, and thereby objective valuation of the proposed processes by assessing model fit. However, the approach is also limited because of the great complexity underlying human cognition, something that is impossible to capture in a specific model. Below the models used to investigate decisions is outlined.

Cumulative prospect theory

CPT has been formalized as a mathematical model, compromising several free parameters describing the decision making process (Kahneman & Tversky, 1979; Nilsson, Rieskamp, & Wagenmakers, 2011; Prelec, 1998; Tversky & Kahneman, 1992). According to CPT, the subjective value SV of a gamble G is:

$$SV(G) = \sum \pi(p_i)v(x_i), \tag{11}$$

For the current study, the model was extended to incorporate advice as a free parameter allowed to influence the subjective value of a gamble:

$$SV(G) = \sum \pi(p_i)v(x_i) + \omega z, \tag{12}$$

Where ω is a scalar accounting for the possible influence of advice z on the subjective value of a gamble. The advice manipulation was coded -1 if the advice was to reject the gamble, 0 if no advice was present, and 1 if the advice was to accept the gamble. ω would therefore represent the value that would be added or subtracted to the subjective value of the gamble depending on the direction of the advice.

The term π denotes the subjective weighting function of the probability p of outcome i. The weighting function is given by:

$$\pi(p) = \frac{p^c}{(p^c + [1-p]^c)^{1/c}}, \tag{13}$$

Where $c = \gamma$ if the probability is associated with gains, and $c = \delta$ if the probability is associated with losses. Because CPT assumes that the probability weighting function can differ for probabilities associated with gains and probabilities associated with losses, the model have separate parameters.

Similarly to probabilities, the subjective weighting function for values is assumed to differ for gains and losses, and is given by:

$$v(x) = \begin{cases} x^{\alpha}, & x \geq 0 \\ -\lambda(-x)^{\beta}, & x < 0' \end{cases} \tag{14}$$

Where α modulates the curvature of the subjective values for gains, while β modulates the curvature of the subjective value for losses. To maintain the assumptions underlying CPT that the value function for gains follows a concave function, while the value function for losses follow a convex function, these parameters are restricted to the interval $[0, 1]$. As α and β approaches 1, the difference between subjective values and objective values will decrease. λ is a scaling parameter indicating loss aversion. If λ equals 1, it will have no impact on the value function for losses, suggesting no loss aversion. However, if λ is greater than 1, the subjective value of losses will be scaled to have an even larger impact, thereby suggesting loss aversion, which is one of the key assumptions of CPT.

Given equation 11-14 presented above, it is possible to estimate the subjective value of all gambles presented in the experiment. One could therefore assume that the decision maker will accept the gamble if $SV(G) > 0$, and reject the gamble if $SV(G) < 0$. However, such consistent behavior is rarely observed in human behavior. Instead risky choices are assumed to incorporate a certain degree of randomness. Therefore, the suggestion by Nilsson et al. (2011) to incorporate a probabilistic choice rule was used. The choice rule gives the probability of accepting a gamble $p(A)$ based on its subjective value and follows a logistic function:

$$p(A) = \frac{1}{1 + e^{-1 \cdot \varphi \cdot SV(G)}}, \tag{15}$$

Where φ modulates the curvature of the choice rule. For instance, if $\varphi = 0$, responses will be random since $p(A) = .5$. The greater φ exceeds 0, the greater the responses will be determined by the subjective value $SV(G)$ of the gamble.

To summarize, the CPT model includes seven parameters. ω denotes advice. γ and δ denotes the curvature for the probability weighting function for gains and losses, respectively. α denotes the curvature for the weighting function for gains, while β denotes the curvature for the weighting function for losses. λ denotes loss aversion, while φ denotes the extent to which choices is governed by subjective values. Together these parameters determine the probability that a decision maker will accept a given gamble.

Heuristic models

As opposed to CPT, the two proposed heuristic models suggest a much simpler decision making process. The first model, heuristic probability (HP), assumes that the subjective value of a gamble $SV(G)$ is based solely on the difference in probabilities for the positive outcome and the negative outcome:

$$SV(G) = p\left(x_{gain}\right) - p(x_{loss}), \tag{16}$$

Consequently, a gamble where the probability of gain is larger than the probability of loss will have a positive value, and vice versa. A similar choice rule to that of the CPT model was used, were the probability of acceptance follows a logistic function:

$$p(A) = \frac{1}{1 + e^{-1 \cdot \rho \cdot SV(G)}}, \tag{17}$$

Where ρ modulates the curvature of the choice function. If ρ equals 0 it means that the decision maker are not influenced by the differences in probabilities for gains and losses. However, as ρ exceeds 0, the decisions maker will be more guided by the differences in probabilities.

The second model, heuristic magnitude (HM), assumes that the subjective value of a gamble $SV(G)$ is based solely on the sum of the positive outcome and the negative outcome:

$$SV(G) = \sum (x_{gain,} - x_{loss}), \tag{18}$$

Consequently, for a gamble where the gain value is larger than absolute loss value, the sum will be positive, and vice versa. The same choice rule as for the HP model where used to describe to what extend the decision makers probability of accepting a gamble is guided by the sum of the values in the gamble. However, the scaling parameter for the curvature of the choice function is denoted τ instead of ρ.

Statistical estimation of model parameters

When data are nested within subgroups of the entire dataset, accuracy can be improved by modeling the multiple levels of information (Greenland, 2000) This class of statistical models is often referred to as hierarchical models or multilevel models (Gelman & Hill, 2007). The data analyzed in this paper follows such a structure: data points are measured within subjects at the first level, and subjects within the group of subjects at the second level. This motives estimation of parameters both at a subject-level as well as at a group-level. Nilsson et al. (2011) proposed a hierarchical model based on Bayesian methods for estimating the parameters compromising CPT and created a program in WinBUGS for estimation of model parameters. Through simulation they showed that their model was able to accurately estimate the parameters of interest. For the current application I modified the model proposed by Nilsson et al. (2011) to fit the current experiments, and also modified the WinBUGS code to allow estimation of parameters. A hierarchical approach was also used to estimate the parameters underlying the heuristic models.

Bayesian modelling

All analysis in the current paper was based on Bayesian statistical procedures. In Bayesian statistics, parameters themselves are considered random variables (Gelman & Hill, 2007). Bayesian estimation requires definition of uncertainty about parameters before the model is fit to the data. This is known as prior distributions. In this paper, all prior distributions were modeled as uninformative, so that their influence on the later parameter estimates was minimal. This was done by setting their range of uncertainty clearly wider than the range of reasonable values of the parameters. The goal of Bayesian estimation is to obtain the posterior distribution of the model parameters. The posterior distribution describes uncertainty in parameter estimates given observed data, and can thus be used for inferential purposes (Gelman & Hill, 2007). In the current paper, posterior distributions were approximated through Marcov-Chain Monte-Carlo (MCMC) techniques, which allow sampling from the posterior distribution. The model implementations relies on WinBUGS (D. Lunn, Spiegelhalter, Thomas, & Best, 2009; D. J. Lunn, Thomas, Best, & Spiegelhalter, 2000). WinBUGS is a general purpose statistical software for Bayesian analysis that uses MCMC techniques to sample from the posterior distribution of the model parameters. The package R2WinBUGS (Sturtz, Ligges, & Gelman, 2005) was used to run WinBUGS through the statistical software R (R Core Team, 2014).

Results

Parameter recovery study

Because the current application extended the CPT model, a parameter recovery study was performed to ensure that the model were able to adequately recover parameters from a simulated dataset where the true parameters are known. Three simulations were done, only differing in their sample size. The first used the same sample size as in the experiments (N = 45). The two last simulations used larger sample sizes (N = 100 & N = 200) in order to reduce the influence of random error in data, and thereby give an indication of whether the method yields unbiased estimates.

The CPT model is thoroughly described by Nilsson et al. (2011) and will therefore not be fully outlined here. For the simulation study, the only difference made was to extend the model to incorporate advice ω. Individual advice parameters were assumed to come from a group level normal distribution, $\omega_i \sim N(\mu^{\omega}, \sigma^{\omega})$. Prior distributions for the group level mean, μ^{ω}, and standard deviation, σ^{ω}, was set to be uninformative. The mean was described with a normal distribution, $\mu^{\omega} \sim N(0{,}100)$. The standard deviation was described with a uniform distribution $\sigma^{\omega} \sim U(0{,}100)$, which is typically considered uninformative since extreme values are considered apriori equal to more reasonable values (Gelman & Hill, 2007).

The hierarchical models implemented in this study make assumptions about the structure of the data. Instead of assuming that all participants have the same true parameter values, it is assumed that participants have individual parameter values coming from a distribution of true parameter values. This introduces two levels of error; the estimate for a given subject o_i is sampled e_i from a distribution with a true parameter θ_i, and this true parameter is again sampled ε_i from a distribution over all true parameters with mean μ^{θ}. This data structure was implemented in the data generation.

$$o_i = \theta_i + e_i = \mu^{\theta} + \varepsilon_i + e_i, \tag{19}$$

To assess performance of the model, 112 responses from each of 45, 100, and 200 fictive subjects were simulated. Data were simulated using the same gambles as those presented in the real experiments. The true parameter values were based on those reported by Tversky and Kahneman (1992). For each fictive subject, parameter values were drawn from the following distributions: $\alpha_i \sim N(.88, .05)$, $\beta_i \sim N(.88, .05)$, $\gamma_i \sim N(.61, .05)$, $\delta_i \sim N(.69, .05)$, $\lambda_i \sim N(2.25, .10)$, $\varphi_i \sim N(1.5, .10)$, and $\omega_i \sim N(.5, .10)$. These parameters were used to calculate the subjective value for each gamble (i.e., equation 11-14 above). Trial specific responses was then simulated from the Bernoulli distribution with probability of accept given by the inverse logit transformation of the subjective value. Note that the method will only produce a sample, so that random error contributes to data both within subjects and between subjects. Perfect recovery of parameters is thus not expected no matter how accurate the estimation procedure is.

Posterior distributions for each simulation were approximated by a total of 30000 MCMC samples from 3 chains. The first 5000 estimates from each chain were excluded in order to obtain more representative starting value. Chain-convergence was assessed by computing the $\hat{R}$ statistic (Gelman & Rubin, 1992) and visual inspection of trace plots for all posterior distributions. All diagnostics indicated that the chain had converged. $\hat{R}$ was below 1.1 for all parameters and there were no indication of the chain being stuck in particular areas of the parameter space as indicated from the trace plots. Additionally, auto-correlations were virtually non-existent at lag from 1 to 50, indicating good mixing of the chain.

Table 1 summarizes the main results from each of the simulation studies. The data is summarized with the mean and standard deviation (SD), of the posterior distributions for all parameters at the group-level of the model. Figure 4 shows the true distribution of parameters and the posterior distributions of the recovered parameter estimates from all three simulations.

Table 1.

Results from parameter recovery study. Table presents mean point estimate for the recovered parameter estimates with standard deviations in parenthesis. Rows represent each of the simulation studies with differing number of simulated subjects (N).

	Parameter						
	α	β	γ	δ	λ	φ	ω
	.88 (.05)	.88 (.05)	.61 (.05)	.69 (.05)	2.25 (.10)	1.50 (.10)	.50 (.10)
N = 45	.92 (.03)	.90 (.04)	.73 (.05)	.93 (.03)	2.45 (.34)	1.14 (.09)	.72 (.20)
N = 100	.84 (.04)	.91 (.03)	.90 (.04)	.88 (.03)	2.19 (.26)	1.20 (.11)	.55 (.14)
N = 200	.87 (.04)	.90 (.03)	.85 (.03)	.84 (.02)	2.29 (.31)	1.16 (.10)	.57 (.13)

First, consider the value function parameters α and β. Both their mean and variability, as indicated by their SD, are near to perfect recovered in all three simulations. Recovery of the mean for the probability weighting parameters γ and δ is not as satisfactory as the value function parameters. The mean of both parameters tend to be overestimated, but the variability is reasonably recovered. The loss aversion parameter λ seem to be adequately recovered if one consider the estimates of the mean, and seem to be improving as a function of larger sample sizes, as one should expect from an unbiased estimator. However, its variability is quite overestimated, with a factor of about 3. Since CPT is mostly used as a descriptive model of the decision making process, as is the case in the current paper, estimates of the mean are more important than estimates of variability, since these serve as point estimates for the parameters. The sensitivity parameter *φ* seems to be systematically underestimated, as is evident by estimates not improving as a function of sample size. However, the SD estimates are near to perfect. The advice parameter *ω* are recovered with an satisfactory error rate. Estimates of both mean and SD are quite good under all simulations, and both seem to improve as a function of sample size.

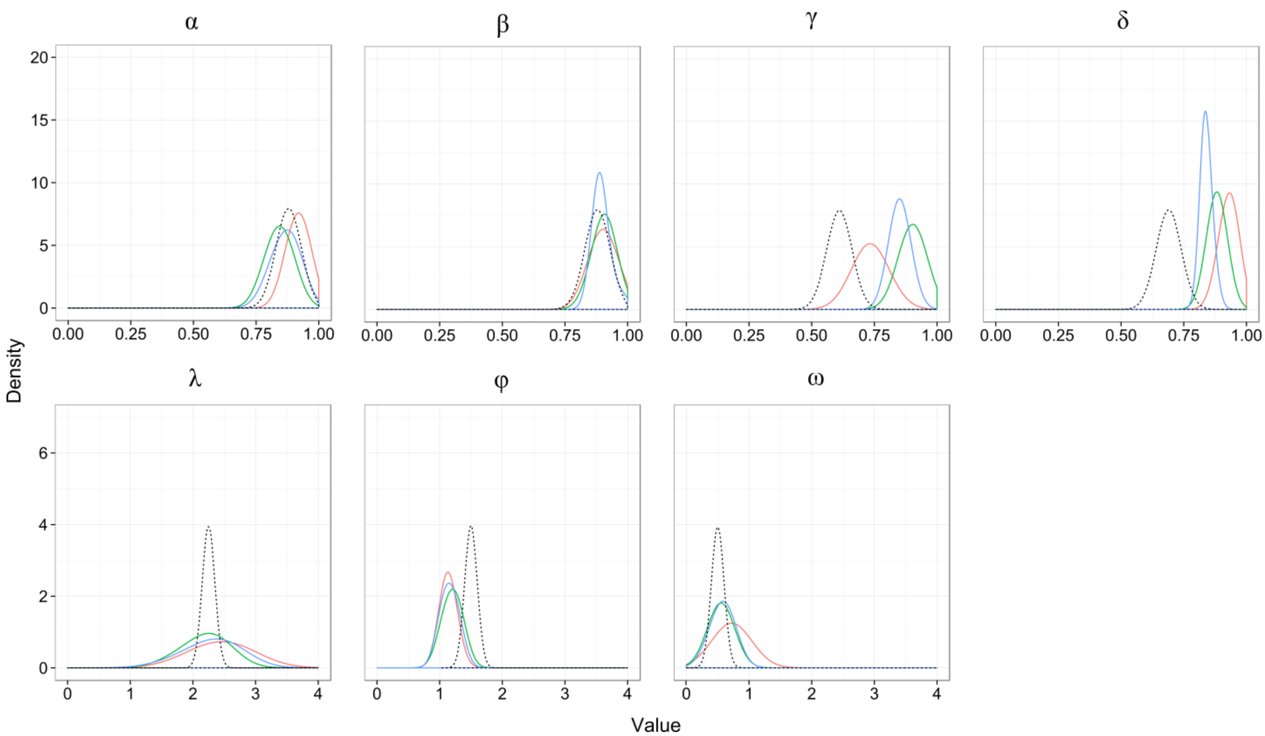

Figure 4. Posterior distributions of the group-level means under each simulation. The dotted lines represent the true distribution used to generate the data. The red lines represents the posterior distributions from the simulation when N = 45. The green lines represents the posterior distributions from the simulation when N = 100. The blue line represents the posterior distributions from the simulation when N = 200.

Overall, most parameters seem to be adequately recovered. Systematic deviations appeared for the probability weighting parameters γ and δ, as well as the sensitivity parameter φ. It should however be emphasized the current parameter recovery study is not adequately suited to separate random error from systematic error, and it is therefore not appropriate to draw strong conclusions about whether estimators are biased. It should also be noted that CPT is a complex model, which inevitably makes parameter estimation difficult (Nilsson et al., 2011). Overall, results resemble those from Nilsson et al. (2011).

Training

Before fitting the decision making models to the experimental data, I investigated accuracy levels across training trials. The training trials were included in order to reduce unwanted training effects during the main experiment, but also to ensure that participants properly understood the task. Accuracy levels from the training sessions therefore serve as exclusion criteria for participants not understanding the task. Accuracy was operationalized as to what extent choice behavior conformed to what would be predicted from the expected payoffs of the gambles. A gamble with a positive payoff should thus be accepted, while a gamble with a negative payoff should be rejected. Here, accuracy for gambles with 0 in expected payoff stays undefined and such trials were therefore excluded from the analysis.

Accuracy was assessed using a hierarchical Bayesian model, with a binomial link function between the model and the accuracy levels as the response variable. Individual accuracy levels, θ_i, were transformed with a logit transformation, assumed to come from a group level normal distribution, $\theta_i \sim N(\mu^\theta, \sigma^\theta)$. Prior distributions for the group level mean, μ^θ, and standard deviation, σ^θ, was set to be uninformative. The mean was described with a uniform distribution, $\mu^\theta \sim U(0,1)$, thus considering all accuracy levels equally likely apriori. The standard deviation was also described with a uniform distribution, $\sigma^\theta \sim U(0,100)$.

Posterior distributions were approximated by a total of 30000 MCMC samples from 3 chains, were the first 5000 samples were discarded in order to obtain more representative starting values. Chain convergence was assessed by computing the $\hat{R}$ statistic, visual inspection of trace plots, and by investigating autocorrelations up to 50 lags. $\hat{R}$ was below 1.05 for all parameters and there was no indication of the chain being stuck in particular areas of the parameter space. Additionally, autocorrelations were virtually non-existent, indication good mixing of the chain.

Results showed that at the group-level, accuracy levels were high (M = .96) with low inter-individual variability (SD = .04). These results indicate that most participants properly learned the task. To assess individual accuracy levels, the posterior distribution for each individual were evaluated against what would be expected from random responding (i.e., $\theta_i =$ .5). Inferences about whether accuracy reached satisfactory levels were made by evaluating whether the 95% highest density interval (HDI) of the posterior distribution excluded .5. The HDI refers to the 95% of the posterior distribution with the highest density, and can be interpreted as the 95% most likely parameter values. The HDI share many properties with a parametric confidence interval, but will differ for distributions not symmetrical about the mean. In Bayesian statistics, the HDI is a common summary of the posterior distribution (Kruschke, 2010). The 95% HDI was not above .5 for three participants (see appendix B and figure 5). These were excluded from further analysis of the main experiments.

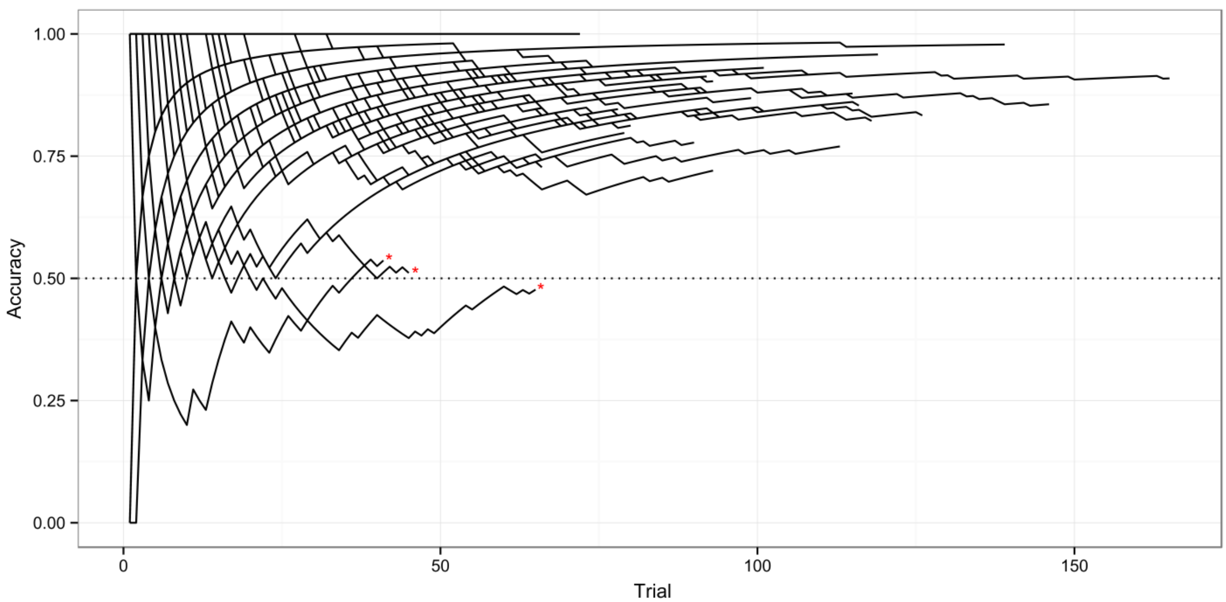

Figure 5. Running means plot of cumulative accuracy across trials for each participant. The dotted line represents expected accuracy if responses were guided by a random process. Lines marked with a red asterix indicate accuracy levels of participants whom were excluded from further analysis. As is evident from the figure, these participants deviated greatly from the general levels of accuracy.

Experiment

For the analysis of the data from the experimental trials, three subjects were excluded, leaving 42 participants for the subsequent analysis. The goal of the first analysis was to fit the CPT model to choice preferences under high time-pressure and low time-pressure. The only difference in the model from the simulation study was that parameters were estimated simultaneously under high and low time pressure.

To fit the CPT model, a total number of 30000 MCMC samples from 3 chains were obtained to approximate the posterior distributions. Chain convergence was assessed by computing the $\hat{R}$ statistic, visual inspection of trace plots for all parameters, and by investigating autocorrelations up to 50 lags. $\hat{R}$ was below 1.1 for all parameters, there was no indication of the chain being stuck in particular areas of the parameter space, and autocorrelations were non-existent.

Table 2 summarizes the main results from fitting CPT under conditions of high time-pressure and low time-pressure. Table 2 shows the mean point estimate and SD in parenthesis for the estimated group-level parameters of the CPT model.

Table 2

Results from fitting the CPT model to the experimental data. Mean point estimate and standard deviations enclosed in parenthesis for the group level parameters under conditions of high time pressure and low time pressure.

	Parameter						
	α	β	γ	δ	λ	φ	ω
High time pressure	.43 (.05)	.26 (.05)	.86 (.04)	.44 (.04)	2.08 (.25)	2.72 (.35)	.16 (.15)
Low time pressure	.72 (.05)	.55 (.06)	.84 (.04)	.69 (.05)	1.52 (.14)	2.45 (.34)	.18 (.15)

The first notable aspect of table 2 is that except for γ and φ, all mean point estimates are lower for decisions made under high time-pressure than decisions made under low time-pressure. To evaluate these differences, the posterior distribution for each parameter under high time pressure was subtracted from the posterior distribution of the same parameter estimated under low time pressure (see figure 6 below). This procedure accounts for correlations between repeated measures in the variability of the difference scores. Confidence in these differences was established by evaluating whether their 95% HDI excluded 0. An index of confidence that the difference is unequal to 0 was calculated as the proportion of the empirical distribution below or above 0. Reliable differences were found for the gain value parameter α (95% HDI = [.16, .42], p(α|low time pressure > α|high time pressure) = 1.00) as well as for the loss value parameter β (95% HDI = [.16, .44], p(β|low time pressure > β|high time pressure) = 1.00). At the individual level, the direction of the effect (indicated by the mean-difference) for α was the same for 100% of the participants, and for 95% of the participants for β. These results indicate that the weighting of both negative values and positive values decreases in decisions made under high time pressure as compared to decisions made under low time pressure. No difference between high and low time pressure conditions were found for the probability parameter associated with gains γ (95% HDI = [-.14, .09], p(γ|low time pressure > γ|high time pressure) = .36), where 38% of the participants parameter estimates decreased. However, the probability parameter associated with losses, δ was lower under high time pressure than low time pressure (95% HDI = [.14, .37], p(δ|low time pressure > δ|high time pressure) = 1.00). This effect was present for 100% of the participants, indicating that the weighting of probabilities associated with losses decreased under time pressure. In addition, the loss aversion parameter λ, increased as a result of time pressure (95% HDI = [-1.14, 0.00], p(λ|high time pressure > λ|high low pressure) = .98), and this effect was present for 86% of the participants. No difference between the conditions were found for the sensitivity parameter φ (95% HDI = [-1.20, 0.66], p(φ|1ow time pressure > φ|1ow high pressure) = .28) where 40% of the participants decreased under high time pressure. Nor were any difference between the conditions found for the advice parameter ω (95% HDI = [-.38, .46], p(ω|low time pressure > ω|high time pressure) = .55), where 62% the participants decreased under time pressure. Since there were no differences in the advice parameter between the conditions, the advice manipulation will not be further discussed.

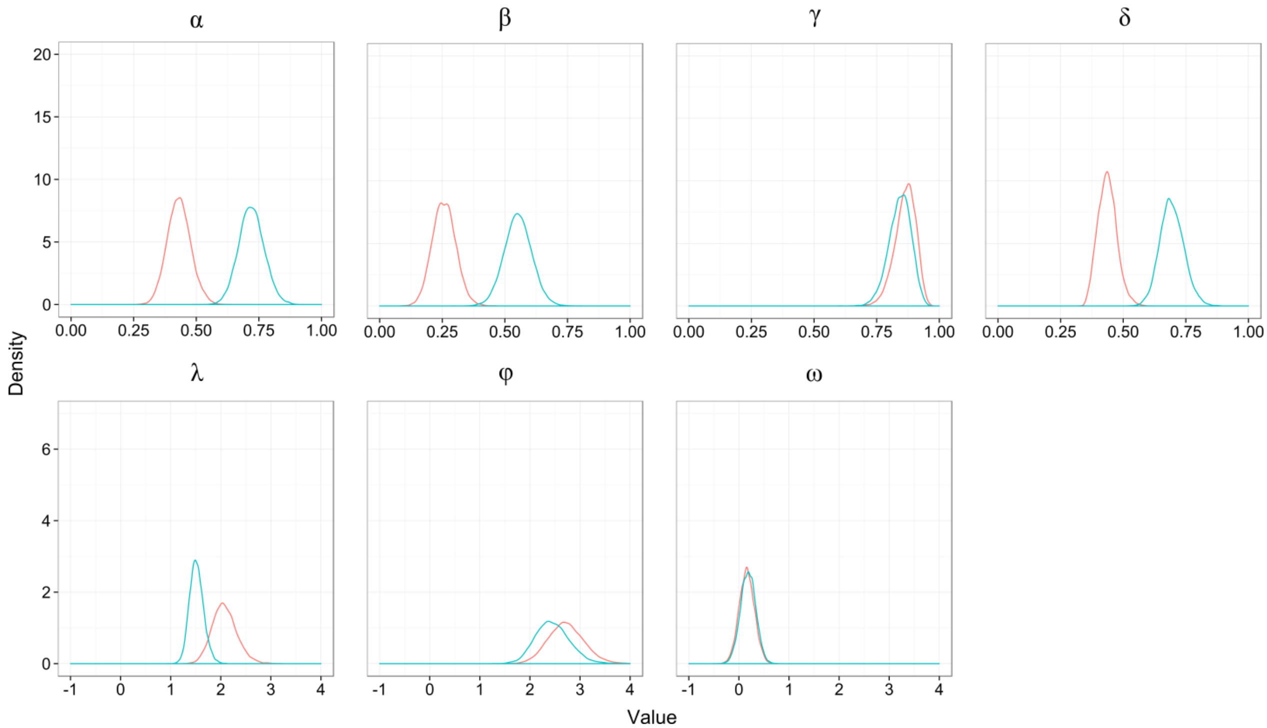

Figure 6. Posterior distributions for the group-level means under conditions of high time pressure and low time pressure. The red lines represent the posterior distributions for the parameter estimates under high time pressure. The blue lines represent the posterior distributions for the parameter estimates under low time pressure.

The second notable aspect of table 2 is that the point estimates for the loss aversion parameter λ is greater than 1 under both conditions, thus indicating a general tendency for loss aversion under both conditions of time pressure. Therefore, it was additionally evaluated if λ was greater than one in each of the time pressure conditions separately. Results showed that loss aversion was present under low time pressure (95% HDI = [1.26, 1.81], p(λ|low time pressure > 1) = 1.00) and under high time pressure (95% HDI = [1.59, 2.55], p(λ|high time pressure > 1) = 1.00). While φ has no direct interpretation on its own, it should be greater than 0 to indicate that choices are not random. Therefore it was also evaluated weather φ was greater than 0 in both conditions separately. Under low time pressure φ exceeded 0 (95% HDI = [1.82, 3.13], p(φ|low time pressure > 0) = 1.00), and under high time pressure φ exceeded 0 (95% HDI = [2.04, 3.44], p(φ|high time pressure > 0) = 1.00).

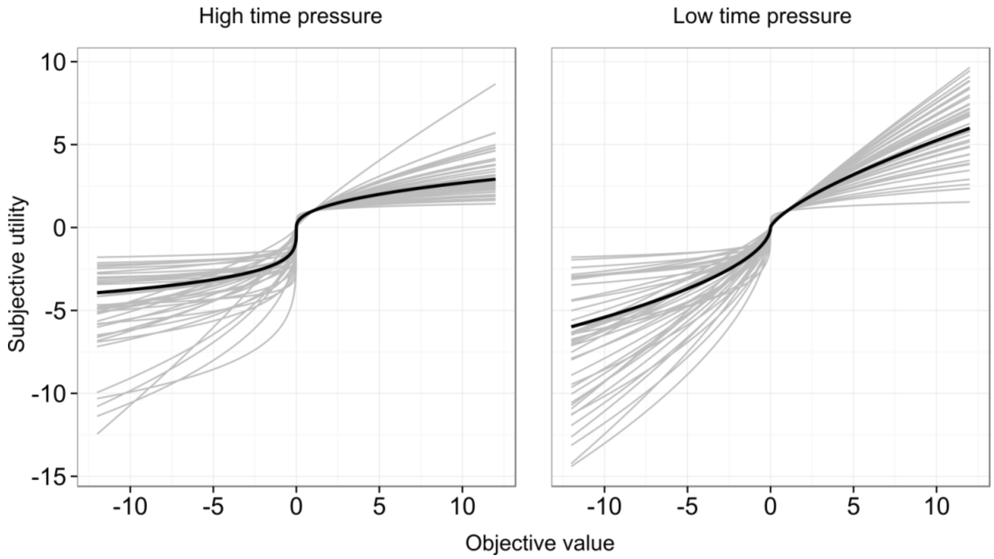

Figure 7. Estimated value functions under both time pressure conditions. The black lines represents the value function estimated from the mean of the group level parameters, whereas the grey lines indicates the value function estimated from the mean of each participant's own parameters.

Using the mean of the parameters α, β, and λ to estimate the value functions show substantial functional changes between conditions (see figure 7). Generally, the value function flattens out as an effect of time pressure suggesting that under time pressure, decision makers is less sensitive to variation in positive and negative values. For instance, the average participant's estimated subjective utility of 5 under low time pressure is $5^{.72} = 3.19$. Whereas the average participant's estimated subjective utility of 5 under high time pressure is $5^{.43} = 1.98$. The same effect is evident for negative values. For instance, the average participant's estimated subjective utility of -5 under low time pressure is $-1.52(- - 5)^{.55} = -3.68$. Whereas the average participant's estimated subjective utility of -5 under high time pressure is $-2.08(- - 5)^{.26} = -3.16$. The results also shows that the absolute utility of -5 is greater than the absolute utility of 5 under both conditions, supporting the assumption of CPT that losses in general are more important for decisions than gains.

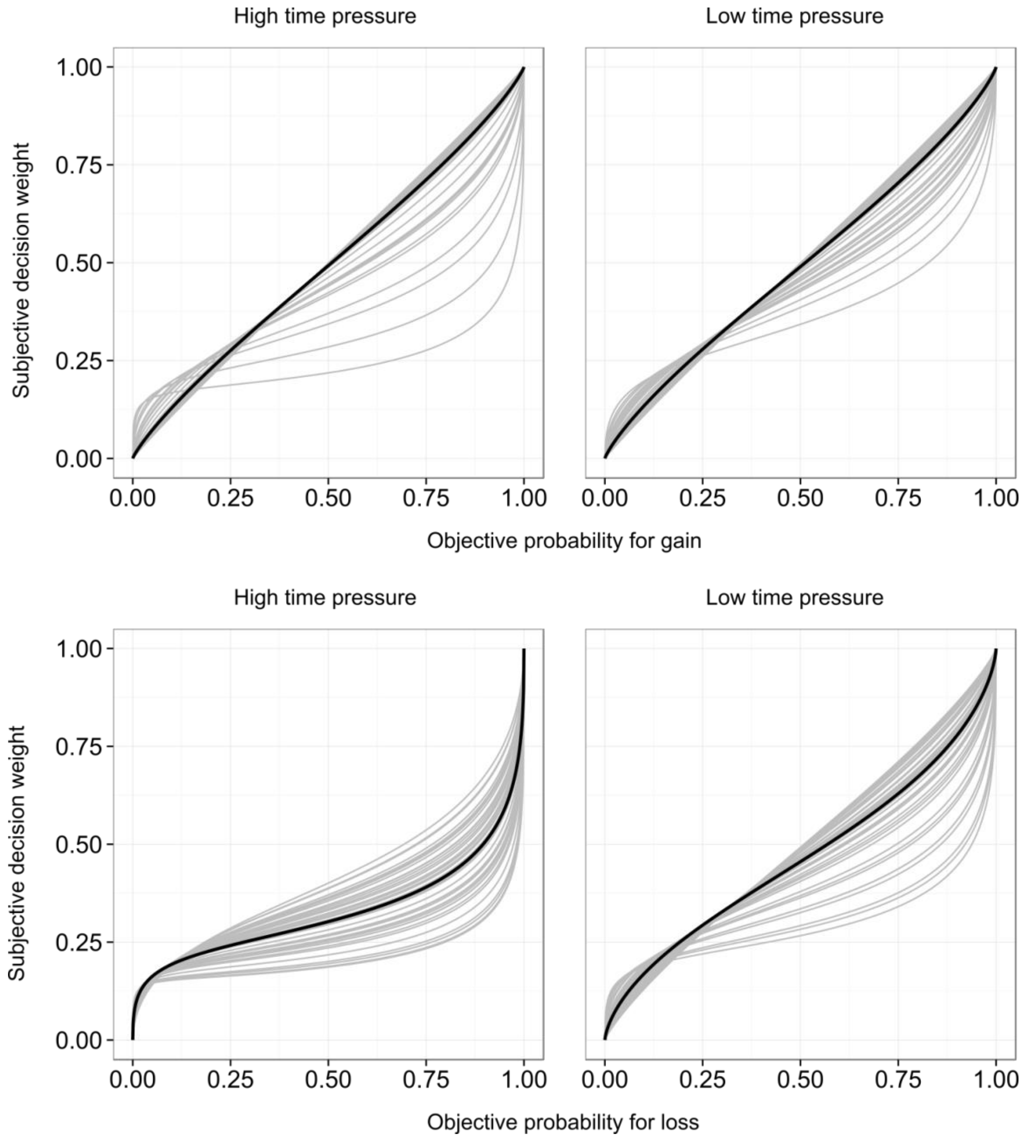

Figure 8. Estimated weighting functions under both time pressure conditions. The black lines represents the weighting function estimated from the mean of the group level parameters, whereas the grey lines indicates the weighting function estimated from the mean of each participant's own parameters. The two upper graphs show the weighting function for probabilities associated with gains. The two lower graphs show the weighting function for probabilities associated with losses.

Using the mean of the parameters γ and δ to estimate the weighting functions under both conditions shows an interesting pattern (see figure 8). Under low time pressure, both functions approach a linear function, indicating that probabilities are weighted close to optimal from an expected utility perspective. However, under high time pressure, only probabilities associated with gains approaches a linear function whereas probabilities associated with losses flattens out.

For instance, under low time pressure, the estimated decision weight for a probability of .8 associated with gains is:

$$\frac{.8^{.84}}{(.8^{.84} + [1 - .8]^{.84})^{1/.84}} = .75, \tag{20}$$

Whereas the estimated decision weight for a probability of .8 associated with losses is:

$$\frac{.8^{.69}}{(.8^{.69} + [1 - .8]^{.69})^{1/.69}} = .67, \tag{21}$$

Both estimates are relatively close to the objective probability of .8, especially the weighting of probabilities associated with gains. Under high time pressure, the estimated decision weight for a probability of .8 associated with gains is:

$$\frac{.8^{.86}}{(.8^{.86} + [1 - .8]^{.86})^{1/.86}} = .76, \tag{22}$$

Very close to the weight under low time pressure. However, the estimated decision weight for a probability of .8 associated with losses decreases:

$$\frac{.8^{.44}}{(.8^{.44} + [1 - .8]^{.44})^{1/.44}} = .42, \tag{23}$$

The results suggests that under low time pressure, participants is sensitive to probabilities associated with both gains and losses, but under high time pressure, their sensitivity decreases substantially for probabilities associated with losses, but not for gains.

Evaluating these results together, one pattern emerges. Under high time pressure participants seem to be less sensitive to all information except the probability of gains. That is, the subjective values for both gains and losses decreases, and the decisions weight for probabilities associated with losses decreases. No such effect was found for probabilities associated with gains.

Model comparison

The goal of the second analysis of the experimental data was to fit the simpler models representing a heuristic decision making process, to the data. Thereby allow assessing whether either of these adequately described decisions made under high time pressure.

Both the HP and the HM model were fitted as hierarchical models, with a Bernoulli distribution as the link function between the model and the choice preferences as response variable. At the individual level, both the HP and the HM model only have one parameter ρ and τ, which is a scalar for the predictor variable representing the heuristic decision rule.

Both parameters were assumed to come from group level normal distributions, $\rho_i \sim N(\mu^\rho, \sigma^\rho)$ and $\tau_i \sim N(\mu^\tau, \sigma^\tau)$. Prior distributions for the group level means was described with uninformative normal distributions, $\mu^\rho \sim N(0,100)$ and $\mu^\tau \sim N(0,100)$. Standard deviations were described with uninformative uniform distributions, $\sigma^\rho \sim U(0,100)$ and $\sigma^\tau \sim U(0,100)$.

Posterior distributions were approximated by a total of 30000 MCMC samples obtained from three chains, were the first 5000 samples in each chain were discarded in order to obtain more representative starting values. Chain convergence was assessed by computing the $\hat{R}$ statistic, inspection of trace plots, and by investigating autocorrelations up to 50 lags. $\hat{R}$ was below 1.01 for all parameters. There was no indication of the chain being stuck in particular areas of the parameter space and autocorrelations were non-existent.

The parameters of the heuristic models have no direct interpretation on their own, except for their direction and whether they are different from 0. The results showed that the group level estimate of the HP model was well above 0 (M = 3.48, SD = .29, 95% HDI = [2.91, 4.06], p(ρ|high time pressure > 0) = 1.00). The results suggest that as the magnitude of the difference for the probability of gain and the probability for loss increased, participants tendency to accept the gamble increased. The same pattern was found for the HM model (M = .13, SD = .04, 95% HDI = [.05, .20], p(τ|high time pressure > 0) = 1.00), suggesting as the sum of the magnitude for gains and loss increased, participants tendency to accept the gambles increased. Together these results suggest that both proposed heuristic models offer possible explanation for the decisions made under high time pressure.

Table 3.

Results from comparing fit for all models under high time pressure. $\bar{D}$ is the mean of the model-level deviance. p_D is the effective number of parameters in the model. DIC is the model fit statistic.

	$\bar{D}$	p_D	DIC
HM	7703.90	44.29	7748.19
HP	6793.03	38.16	6831.19
CPT	5130.98	273.37	5404.35

To investigate whether decision making under high time pressure could be adequately described by some of the proposed heuristic models, the deviance information criterion (DIC) (Spiegelhalter, Best, Carlin, & Van Der Linde, 2002) was used to index model fit. Table 3 show the main results from evaluating DIC for each of the three models under conditions of high time pressure. Note that DIC is a compromise between the fit of the model and the effective number of parameters defining the model, so that models with many parameters are penalized.

As is evident from table 3, CPT offered a better description of the data than either of the proposed alternative models. Consequently, results do not support the second hypotheses that decision made under high time pressure may be adequately explained by simple heuristic models. However, it is of interest that the model based only on the probabilities of the gambles (HP) offers a much better description of choice preferences than the model based only on the values in the gambles (HM).

Discussion

The goal of the current study was to investigate decisions made under high time pressure as compared to decisions made under low time pressure. For this aim, a probabilistic decision making task was used in two experimental studies. It was investigated whether CPT was able to adequately describe decision under high time pressure, or if a simpler heuristic decision model, that are not a subset of CPT, could adequately describe decisions under time pressure. The latter would imply a shift in decision strategy when people are put under time constraints.

CPT and time pressure

Estimates of several central parameters in the CPT model were lower under high time pressure than under low time pressure. Results showed that under time pressure, the relative weight put on both negative and positive values as well as probabilities associated with losses, decreased substantially. This trend was not observed for probabilities associated with gains for which the decision weights remained the same independent of time pressure. This pattern is evident from figure 7 and 8; the probability of gains and their associated decisions weights is the only relationship approaching a linear function in both conditions. It was also found that loss aversion increased under high time pressure compared to low time pressure.

The results suggest that under time pressure, people ignore, or put less weight on, most information except the probability of gains. These results are in accordance with Maule, Hockey & Bdzola (2000) who found that time pressure led to a decreased influence of negative information on decisions. However, earlier findings (Ben Zur & Breznitz, 1981; Wallsten, 1993) found an increased priority for negative information for decisions made under time pressure. Although these results conflict on which information becomes central under time pressure, all suggest that time pressure leads to unbalanced weighting of the available information. One possible explanation could be that people try to use a truncated version of the integrative approach also under high time pressure, but that there simply isn’t enough time to process more than only a small part of the information. It is still unclear why people systematically base their decisions to a large extend on the probability of positive outcomes, and not for instance, the magnitude of the positive outcome.

Shift in decision making process

Since CPT offered a better description of decisions under high time pressure than either of the proposed simpler heuristics, the results offers no direct support for the hypothesis that time pressure leads to a shift in decision making processes. However, a shift in decisions making strategy under time pressure still seems plausible in light of the results. Several of the studies who have reported a change in decision making strategy have either used a less stringent time limit than the current study (Payne, Bettman, & Johnson, 1988; Svenson et al., 1990), or manipulated time indirectly by imposing cost of being slow (Payne et al., 1996; Rieskamp & Hoffrage, 2008). The current study used a time limit of 2 seconds, which clearly limits the amount of information than can be processed to an even larger extent. As such, it is likely necessary to switch to even simpler decision strategies to adapt to the demanding environment. One such strategy could be to try to avoid losses, instead of trying to maximize income. Such an explanation is supported by the finding that loss aversion increased under time pressure. If people only based their decisions on the probability of gains under time pressure, they effectively exclude many of the situations where the long term payout would be negative. Although not optimal, following such a strategy is clearly better than responding at random, and might serve as an adaptive strategy when situational demands to a large extend limits processing resources.

Limitations

One limitation of the present research concerns the nature of the gambles presented in the experiments. Because real money was used as incentives, it was not possible to investigate decisions concerning actual losses. That is, participants could not actually lose money; they could only reduce their reward. It is possible that situations where actual losses are present might dictate other decision strategies.

There are also inherent limitations in using model comparison as a tool for inferences concerning the underlying cognitive process. Because one model explains data marginally better than others, it does not necessarily mean that this model is the correct and only representation of the true underlying process. Empirical investigations of models explaining cognitive processes will necessitate relatively simple models, and one may thereby not recognize the possibility that several cognitive processes may coexist and interact to produce the observed behavioral responses. As there are undeniable many possible relationships and interactions between time and decision making, it seems unlikely that a single model that may be fitted to observed data, will be able to encompass the complete decision-making system.

Conclusions

By using sophisticated models of the decision making process, the current study may aid a deeper understanding of the effect of time pressure on risky decision making. In summary, the research show that time pressure has a substantial effect on decisions. It was shown that under time pressure, the probability of a positive outcome to a large degree guided decisions while other information was mostly ignored or undermined. It was further shown that CPT offered the best account for decisions under high time pressure than any of the proposed heuristic models.

Although results showed significant changes in parameters of the CPT model when time constraints were introduced, it is still unclear whether this reflects a qualitative change in decision mechanisms, or a more quantitative change in how values and probabilities are integrated. Such conclusion would be more warranted if either of the simpler models had offered a fit comparable to - or better than - CPT under conditions of high time pressure.

The suggested alternative models for decisions made under high time pressure also represent a very small subset of possible alternative models. Besides the models investigated in the current research, there are a number of models describing heuristics types of decision making processes with a solid theoretical foundation (Birnbaum, 2008; Brandstätter et al., 2006; Gigerenzer & Goldstein, 1996; Goldstein & Gigerenzer, 2002; Payne et al., 1996; Rieskamp, 2008). Future investigations of alternative models may support conclusions different from those proposed in the present study.

The same applies to future investigations using other methods. Eye tracking and fMRI should investigate if the results is also supported by processing variables including dwell times, pupil dilation, and representation of gambling information in the brain. Additional behavioral studies and/or computational modeling should further investigate the boundary conditions under which CPT is a good description of risky decision making under time pressure.

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Appendix A: Table of gamble stimuli

The following gambles were used in the two experiments. Those marked with an asterix were excluded from the FMRI experiment. Gain and loss denotes the value of the positive and negative outcomes. P(gain) and P(loss) denotes the probability of the gain value and loss value occurring, respectively.

$No.$	$gain$	$p(gain)$	$loss$	$p(loss)$
1*	12	0.2	-12	0.2
2*	12	0.2	-12	0.4
3	12	0.2	-12	0.8
4*	12	0.2	-3	0.2
5	12	0.2	-3	0.4
6*	12	0.2	-3	0.8
7*	12	0.2	-6	0.2
8*	12	0.2	-6	0.4
9	12	0.2	-6	0.8
10*	12	0.4	-12	0.2
11	12	0.4	-12	0.4
12	12	0.4	-12	0.8
13	12	0.4	-3	0.2
14*	12	0.4	-3	0.4
15	12	0.4	-3	0.8
16	12	0.4	-6	0.2
17	12	0.4	-6	0.4
18*	12	0.4	-6	0.8
19	12	0.8	-12	0.2
20	12	0.8	-12	0.4
21*	12	0.8	-12	0.8
22	12	0.8	-3	0.2
23	12	0.8	-3	0.4
24	12	0.8	-3	0.8
25	12	0.8	-6	0.2
26	12	0.8	-6	0.4
27	12	0.8	-6	0.8
28	3	0.2	-12	0.2
29	3	0.2	-12	0.4
30	3	0.2	-12	0.8
31	3	0.2	-3	0.2
32	3	0.2	-3	0.4
33*	3	0.2	-3	0.8
34	3	0.2	-6	0.2
35	3	0.2	-6	0.4
36	3	0.2	-6	0.8

37	3	0.4	-12	0.2
38*	3	0.4	-12	0.4
39	3	0.4	-12	0.8
40	3	0.4	-3	0.2
41	3	0.4	-3	0.4
42*	3	0.4	-3	0.8
43*	3	0.4	-6	0.2
44	3	0.4	-6	0.4
45	3	0.4	-6	0.8
46	3	0.8	-12	0.2
47	3	0.8	-12	0.4
48	3	0.8	-12	0.8
49	3	0.8	-3	0.2
50*	3	0.8	-3	0.4
51	3	0.8	-3	0.8
52	3	0.8	-6	0.2
53*	3	0.8	-6	0.4
54	3	0.8	-6	0.8
55*	6	0.2	-12	0.2
56	6	0.2	-12	0.4
57	6	0.2	-12	0.8
58	6	0.2	-3	0.2
59*	6	0.2	-3	0.4
60	6	0.2	-3	0.8
61	6	0.2	-6	0.2
62	6	0.2	-6	0.4
63*	6	0.2	-6	0.8
64*	6	0.4	-12	0.2
65	6	0.4	-12	0.4
66	6	0.4	-12	0.8
67	6	0.4	-3	0.2
68	6	0.4	-3	0.4
69*	6	0.4	-3	0.8
70	6	0.4	-6	0.2
71	6	0.4	-6	0.4
72*	6	0.4	-6	0.8
73	6	0.8	-12	0.2
74*	6	0.8	-12	0.4
75	6	0.8	-12	0.8
76	6	0.8	-3	0.2
77	6	0.8	-3	0.4
78	6	0.8	-3	0.8
79*	6	0.8	-6	0.2
80*	6	0.8	-6	0.4

81	6	0.8	-6	0.8

Appendix B: Results from training

The figure show posterior distributions of accuracy levels for all participants from the training session. The dotted lines show the point where responses were considered random (i.e., .5). Participant 18, 20 and 43 were excluded due to unsatisfactory accuracy levels.