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Safe models for risky decisions

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Appendix to Chapter 9: “Bayesian Techniques for Analyzing Group Differences in the Iowa Gambling Task: A Case Study of Intuitive and Deliberate Decision Makers”

In this appendix we describe in detail the experiment that was conducted to obtain the data reported in the main article, and the product space method that was used for the Bayes factor model comparison.

G.1 Experiment

Material

Iowa Gambling Task

The IGT was presented as a computerized task, based on the original version of Bechara et al. (1994).¹ On the computer screen, four decks of cards were presented, labeled “A”, “B”, “C”, and “D”. Participants were initially given a (hypothetical) loan of +2000 Swiss Francs (CHF) and instructed to consecutively choose among the decks, by clicking on one of the decks at each trial, resulting in a draw of a card from the deck, so as to maximize their long-term net outcome (cf. Bechara et al., 1994, 1997). After each selection of a deck, participants received feedback on the gains as well as the losses (if any) associated with the card, and the running tally. The trials were self-paced.

¹In contrast to the payoff scheme introduced by Bechara et al. (1994), we used a stable loss of \$−50 in deck C.

Measurement of decision styles

To measure individual participants’ decision style, we used an inventory compiled by Betsch and Iannello (2010), whose subscales are taken from five different questionnaires: the Rational-Experiential Inventory (REI; Pacini & Epstein, 1999), the Preference for Intuition and Deliberate Scale (PID; Betsch, 2004), the General Decision Making Style (GDMS; Scott & Bruce, 1995) questionnaire, the Cognitive Style Indicator (CoSI; Cools & van den Broeck, 2007), and the Perceived Modes of Processing Inventory (PMPI; Burns & D’Zurilla, 1999). All of these questionnaires measure a person’s tendency to rely on an intuitive and a deliberate decision mode on two separate bipolar subscales. For instance, participants are presented with statements such as “My feelings play an important role in my decisions.” (intuition subscale of the PID), or “Before making decisions, I first think them through.” (deliberation subscale of the PID). At each item, participants are asked to indicate the extent to which the statement represents their opinion (on a scale from 1 = very much disagree to 7 = very much agree). The original versions of the REI, PID and the GDMS contain items that include the term “intuition”. Betsch and Iannello (2010) argued that this might activate different concepts across people. These items were therefore excluded from Betsch and Iannello (2010)’s compiled inventory. Altogether, the questionnaire consisted of 70 items from 12 subscales. As described in more detail below, we distinguished intuitive and deliberate decision makers based on their total scores on these subscales.

Procedure

Participants completed the experiment individually. They signed an informed consent form and started the experiment with the IGT, followed by demographic questions and a computerized version of the decision-style inventory. Then they were thanked, debriefed, and received course credits or a flat fee of 7.50 CHF –a decision that had to be made before the experiment– as well as a performance-contingent bonus from their IGT performance (specifically, final IGT score/1000 * 1.5 CHF).

Table G.1: *Three-factor solution of the principal component analysis. Also reported are Cronbach’s α as a measure of the reliability of each subscale.*

Subscale	Factor		
	Deliberation	Intuition	Spontaneity
Deliberation (GDMS) ($\alpha = .80$)	.890	.009	-.184
Deliberation (PID) ($\alpha = .74$)	.875	-.170	-.094
Knowing (CoSI) ($\alpha = .79$)	.873	-.067	-.126
Rational ability (REI) ($\alpha = .77$)	.820	-.148	.176
Rational engagement (REI) ($\alpha = .81$)	.659	-.105	-.145
Planning (CoSI) ($\alpha = .70$)	.602	-.325	.130
Experiential ability (REI) ($\alpha = .84$)	.058	.870	.165
Intuition (GDMS) ($\alpha = .69$)	-.122	.850	.056
Intuition (PID) ($\alpha = .79$)	-.151	.809	.018
Experiential engagement (REI) ($\alpha = .41$)	-.321	.604	.033
Automatic (PMPI) ($\alpha = .77$)	.114	.126	.897
Spontaneous (GDMS) ($\alpha = .73$)	-.354	.075	.805

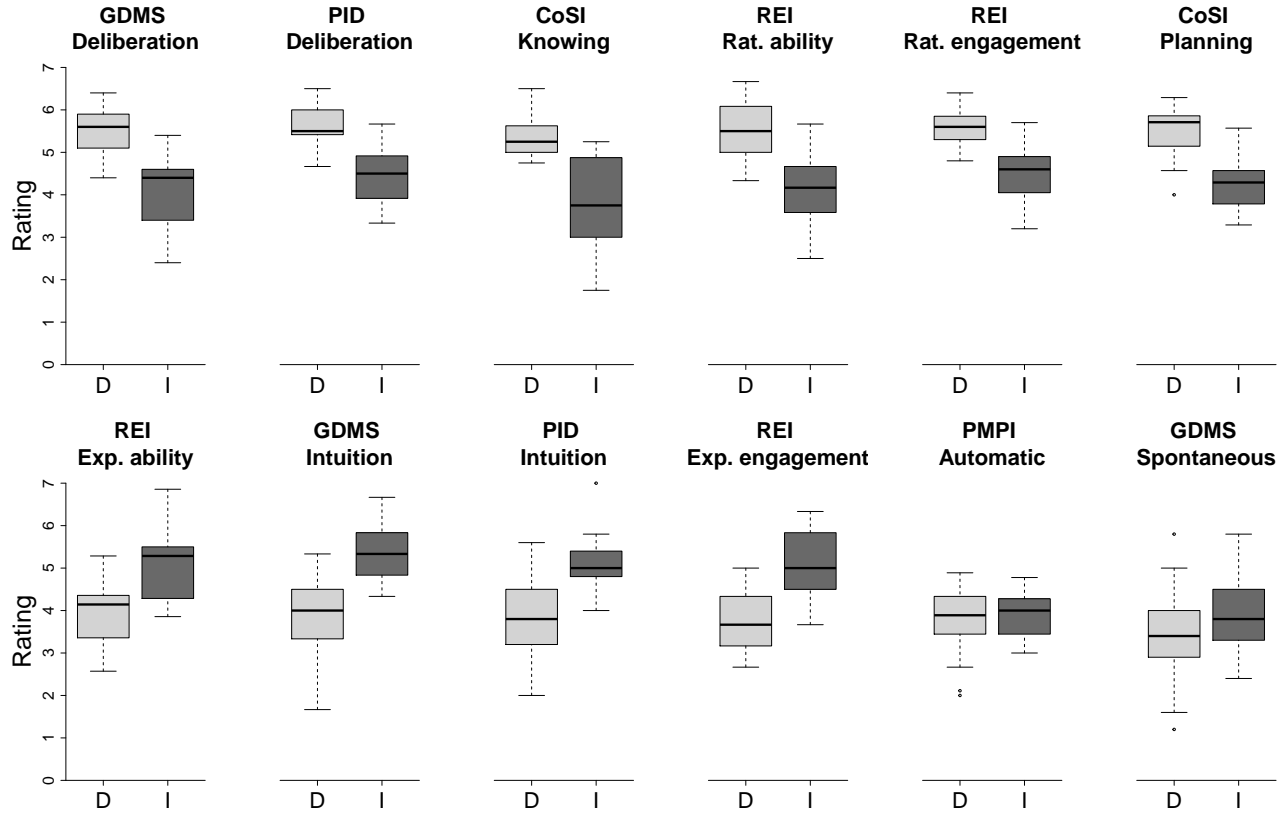


Figure G.1: Distribution of scores on the 12 subscales of the questionnaire compiled by Betsch and Iannello (2010), separately for the deliberate group (i.e., D) and the intuitive group (i.e., I).

Decision Styles

We first determined for each participant the mean score on each of the 12 subscales of the decision-style inventory compiled by Betsch and Iannello (2010). Table G.1 shows that all subscales had acceptable levels of internal reliability, except for the experiential engagement subscale of the REI. However, we decided to keep the experiential engagement subscale in our analyses because excluding it did not lead to different conclusions in the subsequent analyses. Based on each participant's mean score on each of the 12 subscales, we then conducted a principal component analysis with rotation based on the varimax method. The Kaiser criterion suggested a three-factor solution, which accounted for 70% of the total variance. Table G.1 reports the factor loadings of the 12 subscales on these three factors. On the first factor the subscales capturing a deliberate, rational, and planned decision style showed consistently high loadings (deliberation factor). The second factor had consistently high loading for the subscales capturing an intuitive and experiential decision style (intuition factor). The third factor had high loadings of subscales measuring spontaneous decision making (spontaneity factor). Individually, the three factors accounted for 39%, 18.5%, and 12.5% of the variance, respectively.

In the following, we distinguish participants as deliberate or intuitive decisions makers depending on their factor score on the deliberation factor and the intuition factor.² Following previous research (Betsch & Kunz, 2008), we classified participants as intuitive if they had a factor

²Although conceptually similar to “intuition”, based on the factor solution the spontaneity factor seems to

score above the median of the intuition factor and, at the same time, a factor score below the median of the deliberation factor; participants with the opposite pattern were classified as deliberate. This classification scheme yielded 19 participants in the intuitive group and 19 participants in the deliberate group. Thirty-two participants thus remained unclassified. Figure G.1 shows the distribution of scores on the 12 subscales of the questionnaire compiled by Betsch and Iannello (2010), separately for the intuitive and deliberate group. As can be seen, the groups have strongly different profiles on the scales and cover different value ranges.

G.2 Obtaining Bayes Factors with the Product Space Method

In this section we describe how we obtained the Bayes factor with the product space method (Carlin & Chib, 1995; Lodewyckx et al., 2011). The Bayes factor BF_{12} is defined as the change from prior model odds $p(\mathcal{M}_1)/p(\mathcal{M}_2)$ of two models, \mathcal{M}_1 and \mathcal{M}_2 , to posterior model odds $p(\mathcal{M}_1 | D)/p(\mathcal{M}_2 | D)$ brought about by the data D :

$$\underbrace{\frac{p(\mathcal{M}_1 | D)}{p(\mathcal{M}_2 | D)}}_{\text{Posterior model odds}} = \underbrace{\frac{p(\mathcal{M}_1)}{p(\mathcal{M}_2)}}_{\text{Prior model odds}} \times \underbrace{\frac{m(D | \mathcal{M}_1)}{m(D | \mathcal{M}_2)}}_{\text{Bayes factor}} \quad (\text{G.1})$$

For all but the simplest models the Bayes factor cannot be derived analytically. We therefore need a method to approximate the Bayes factor. One such method is the product space method (for alternative methods such as reversible jump, see Green, 2003; Sisson, 2005, and for importance sampling, see Hammersley & Handscomb, 1964; Steingroever et al., 2016; Vandekerckhove et al., 2015). The product space method is a transdimensional Markov chain Monte Carlo (MCMC) method, that is, a method that aims to estimate the posterior model odds for chosen prior model odds (see Equation G.1). This method requires the construction of a “supermodel” encompassing the models to be compared. This “supermodel” is a hierarchical combination of the models to be compared. The hierarchical combination is achieved by a model index that measures the proportion of times that either model is visited to account for the observed data. The prior of the model index corresponds to the prior model odds (i.e., specified before the analysis), and the posterior of the model index corresponds to the posterior model odds. The posterior model index can be estimated by MCMC posterior sampling methods. We can therefore estimate the posterior probability of model \mathcal{M}_k using:

$$\hat{p}(\mathcal{M}_k | D) = \frac{\text{Number of occurrences of } \mathcal{M}_k}{\text{Total number of iterations}}. \quad (\text{G.2})$$

The posterior model probability quantifies the evidence that the data D provide for model \mathcal{M}_k relative to all other models under consideration (Berger & Molina, 2005). Given the estimated posterior model probabilities of two different models, we can estimate the Bayes factor using Equation G.1 because the prior model odds are known (i.e., specified before the analysis).

represent a distinct and orthogonal aspect of people’s decision-mode preferences. To maintain homogeneity with the groups, we did not consider the spontaneity factor in classifying people as intuitive or deliberate decision makers.