Pre-Registration

Analyzing the Impact of Choice Complexity on Personal Risk Choices

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1 Study Information

1. Title (required)	Analyzing the Impact of Choice Complexity on Personal Risk Choices
2. Authors (required)	Maohua Nie, Dr. Sebastian Olschewski, Prof. Dr. Jörg Rieskamp

3. Description (optional)

Individuals make numerous decisions on a daily basis, but often lack the ability to make optimal choices due to the overwhelming amount of information they must process. As cognitive misers, people tend to avoid complex options and prefer simpler and more intuitive alternatives, even if they are not necessarily superior. Previous research has examined the complexity structure of options and has suggested that it can significantly influence individuals' risk choices. Among these studies, compound lotteries are often used as a manipulation of complexity. However, it should be noted that most studies define complexity solely in terms of the number of alternatives or the number of features, and the predominant experimental design involves comparing individuals' preferences for choices with different numbers of potential outcomes. Nonetheless, complexity can also refer to the cognitive effort required to process information, even if the number of potential outcomes remains constant. In other words, options with higher complexity may demand more time and cognitive resources to explore their possible outcomes. Importantly, most of the research on complexity has focused on one type of complexity. In addition, cognitive models have hardly been used to explain people's risky choices. To fill this research gap, our study will employ a series of tasks with different operatinalizations of complexity to examine whether individuals' risk choices are affected by differences in complexity resulting from variations in cognitive burden. We will utilize a series of binary decision problems, such as compound lotteries, to manipulate the complexity involved in calculating each outcome and its respective probability. Such design ensures that we can test whether different forms of complexity can have similar effects on people's risky decisions. Furthermore, We will try to develop models in the framework of drift diffusion model, which has not been used widely in prior studies, to analyze the experimental data. The diffusion model is a model of a cognitive process involving a simple two-choice decision, it assumes that the decisions are made in a noisy process, in which people accumulate information over time from a starting point toward one of two options and begin to respond when one of these boundaries is reached. The model is well suited for fast binary choices. Thus, within the framework of the diffusion model, we believe that our analysis of risky choices will be more reliable and robust, and will allow us to learn about people's cognitive paradigms when faced with options of different complexity.

4. Hypotheses

Behavioral Hypothesis: In the context of decision-making under risk, individuals exhibit complexity aversion, systematically undermining the value of complex options in comparison to their simpler counterparts. Consequently, when presented with two alternatives of comparable value, individuals not only lean towards the simpler choice but also demonstrate shorter decision-making times.

First hypothesis: Complexity aversion is driven by a pre-valuation bias, whereby individuals exhibit a preliminary disposition against complex options prior to the accumulation of substantial information.

Second hypothesis: Complexity aversion is also influenced by a discounting effect that occurs during the information processing stage of decision-making. This effect results in the perceived value of complex options being subjectively reduced or "discounted".

Third hypothesis: Complexity aversion is further exacerbated by challenges in the subjective representation of probability during decision-making processes. Individuals, due to limited cognitive resources or unwillingness, often fail to accurately interpret or consider probabilistic information associated with complex options.

Optional Hypothesis of cognitive ability:
The effect of complexity aversion on decision-making is moderated by individual differences in cognitive ability. Specifically, individuals with higher cognitive abilities are less susceptible to complexity manipulation.

2 Design Plan

5. Study type (required)

Example: Experiment - A researcher randomly assigns treatments to study subjects, this includes field or lab experiments. This is also known as an intervention experiment and includes randomized controlled trials.

6. Blinding (required)

For studies that involve human subjects, they will not know the treatment group to which they have been assigned. Personnel who interact directly with the study subjects (either human or non-human subjects) will not be aware of the assigned treatments. (Commonly known as “double blind”)

7. Study design (required)

Within-subject design.
All Participants will have two main experiment blocks, in both blocks they have to make decisions between two lottery options. There are two types of lotteries – simple and complex. The simple lotteries consist of two outcomes with corresponding probabilities. The complex lotteries also consist of two outcomes, but will involve two steps and require participants to perform calculations to determine the final outcomes and probabilities. We will also include other manipulation of complexity in the following studies. All pairs of lottery options will have different level of characteristics, which contains EV difference (-20, -10, 0, 10, 20), SD difference (15, 10, 5) and skewness difference (no skewness, right skewed vs. left skewed and left skewed vs. right skewed)
In one main block, the two lotteries are always in same kind, namely easy option vs. easy option or complex vs. complex option. In the other block there will be lotteries in different kind, namely easy option vs. complex option or complex option vs. easy option. For all trials, the two lottery options will always be presented simultaneously.
After the main blocks, participants will also complete two cognitve ability tasks.

8. Randomization (optional)

The following structure will be fully randomised:
- Order of two main blocks
- Order of trials within each block
- order of two lotteries within each block

3 Sampling Plan

9. Existing data (required)

Registration prior to creation of data

10. Data collection procedures (required)

The online parts of this research will involve recruiting participants through advertising on Prolific.co. We will only recruit participants with good records, such as a 95% approval rate. Recruitment will commence once we receive ethic approval and finalize the experiment webpage. The in-person studies will take place in the Department of Economics at the University of Basel. We will recruit current or former students of the University of Basel as our participants.

For the online studies, participants who successfully complete the experiment will be compensated at a rate of \$10 per hour, in addition to receiving a monetary bonus. At the end of the experiment, a choice problem will be randomly selected and performed based on the participant's chosen option. The outcome of this selection will determine the bonus payment, which is expected to be approximately \$5. Consequently, participants can expect to receive an average total payment of \$15 per hour, with a minimum payment of \$10 per hour guaranteed in the absence of a bonus. It is important to note that this total payment surpasses the minimum wage per hour for participants in the United States, which stands at \$7.25 per hour and \$8 for participants in Prolific.

In the case of in-person studies, participants will be presented with the choice of either receiving course credit or a flat payment. The bonus payment structure remains consistent with that of the online studies. Our estimation suggests that participants in in-person studies will receive an average payment of CHF 23 per hour, along with a CHF 5 bonus. These reward amounts have been determined based on previous study experiences. Moreover, we maintain flexibility to adjust the reward amounts within a reasonable range, if necessary. Additionally, it is worth mentioning that the total payment for participants in the lab studies exceeds the minimum wage per hour set in the canton of Basel-Stadt (CHF 21.45 per hour). Participants are allowed to participate in the study until the specified sample size is reached.

11. Sample size (required)

Our project sample should be around 83 participants for lab and online studies. We will attempt to recruit up to 90, assuming that not all will complete the task correctly.

12. Sample size rationale (optional)

In previous studies examining the effect of task complexity on choice behaviour of decision maker facing risky options, researchers identified a medium to large effect size (around 0.5, see experiment 2 of Oberholzer et al., 2021). However, we anticipate a smaller effect size in our study. Consequently, we adjusted the effect size to 0.4 by multiplying the effect size by 0.8. To determine the appropriate sample size for our research, we conducted a power analysis using the *pwr* package in R (Champely et al., 2017). This analysis suggested a sample size of 83 (rounded up from 83.34) to achieve 95% power ($alpha = .05$, $d = 0.3996$, two-sided) based on a one sample t test comparing the mean choice proportion of complex options against the 50% benchmark.

We acknowledge the possibility of incomplete responses or the necessity to exclude participant data based on our exclusion criteria. To account for this, we plan to recruit 90 participants initially through Prolific.co. Recruitment will be stopped once the initial sample meet our required sample size. If, however, participant exclusion is higher than anticipated, we will resume recruitment in increments of 5 participants, continuing until we reach our necessary sample threshold.

4 Variables

13. Manipulated variables

Gamble EV (one level) – 30-200
Complexity (two levels) – simple (2 outcomes, direct probability) and complex (2 outcomes, indirect probability)
Variance (SD - three levels) – low (5), medium (10), high (15)
EV Difference (five levels) - 20, -10, 0, 10, 20

Skewness (three levels) – left vs. right, no, right vs. left

14. Measured variables

Choice Task
- Choices
- Reaction time
- Manipulation Check: MCT about instructions)

Cognitive Ability Task
- Number of correctly solved matrices and questions

At the end of the experiment:
- Demographics (Age, Gender, education level)
- Comments

Overall:
- Duration of each element (reaction times)

5 Analysis Plan

15. Statistical models (required)

Analysis 1:
one sample t test comparing the mean choice proportion of complex options against the 50% benchmark for trials in easy vs. complex and complex vs. easy conditions. Expected results: The choice proportion of complex option will significantly different from 50%.

Analysis 2:
Multilevel linear regression (random intercept) predicting reaction time in easy vs. complex and complex vs. easy conditions, with the following predictors:

$$RT = \beta_1 \cdot choice + \beta_2 \cdot EV\_Diff + \beta_3 \cdot EV\_Diff\_2 \tag{1}$$

EV_Diff: expected value difference between option A and B (EVA - EVB)
EV_Diff_2: Square of expected value difference between option A and B
$choice$: dummy coding for choice made my participants (1 for complex option)
Expected results: β_1 should be positive, β_2 and β_3 should be negative.

Analysis 3:
Multilevel logistic regression predicting easy choice (0=complex, 1 = easy) with the following predictors (easy vs. complex and complex vs. easy conditions):

$$p = \beta_1 \cdot EV\_ec + \beta_2 \cdot Var\_diff + \beta_3 \cdot Skew\_rl + \beta_4 \cdot Skew\_lr \tag{2}$$

EV_ec: expected value difference between easy and complex option (EV_Easy - EV_complex)
Var_diff: Standard Deviation difference
$Skew\_rl$: dummy coded for condition right vs. left skewed
$Skew\_lr$: dummy coded for condition left vs. right skewed
Expected results: β_1 should be positive. β_2 should be negative(?), β_3 and β_4 should be...

Modeling methods

Hierarchical drift diffusion models will be fit to behavioral data using the rstan package for R (Stan Development Team, 2023).
Model parameters include: t (non-decisional time), z (starting point, 0 if neutral), a (choice boundary), v (drift rate) and $beta$ (discounting effect).
We will look at 95% CI of each parameter. Based on the hypotheses, we will compare the performance of different models using DICs or WAICs.

The details of models remain under development.

16. Transformations (optional)

17. Inference criteria (optional)

As far as possible, we rely on Bayesian Statistics (95%-Credible Intervals).

18. Data exclusion

Exclusion:
Participants:
1. unsuccessful manipulation check (total attemps > 6)
2. Less than 6/8 accuracy in control trials
3. completing the experiment too fast (1/4 of mean time) or too slow (three times of mean time)
Other not allowed behaviours (e.g., restarting the experiment)

data points:
1. All trials that has reaction time in the range of 0%-2.5% and 97.5%-100% in each condition
2. All trials that has reaction time less than 1 second

19. Missing data (optional)

20. Exploratory analysis (optional)

Cognitive Ability and Complexity Aversion
Hypothesis: People who have higher cognitive ability will be less affected by the complexity.
Multilevel logistic regression predicting easy choice (0=complex, 1 = easy) with the following predictors (only for condition with different kinds of stimuli):

$$p = \beta_1 \cdot EV\_diff + \beta_2 \cdot Var\_diff + \beta_3 \cdot Skew\_rl + \beta_4 \cdot Skew\_lr + \beta_5 \cdot CA \quad (3)$$

CA: cognitive ability tests score (mean score of the two tests)
Expected results: β_5 should be negative.

6 Other

21. Other