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Risk-preferences under cognitive load: A test of theoretical predictions about perceptual biases as an explanation for normative choice deviations.

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Abstract

Expected utility theory predicts that humans, when offered with two prospects, choose the one that offers a higher expected utility. However, there is a large body of literature showing that people do not, in fact, behave in this way. The revolutionary and Nobel Prize winning Prospect Theory provides a descriptive pattern that accounts for those deviations from normative decision-making (Kahneman and Tversky, 1979). However, this descriptive theory does not provide any explanation for why those deviations occur. Recent theories derived from ideas of how perceptual biases may arise from inefficient neural coding have proposed a mechanistic explanation for the pattern of choice behavior described in Prospect Theory (Woodford, 2012; Khaw, 2017). In the present study, we sought to test the predictions of this theory by manipulating the amount of cognitive resources available to participants at the time of choice by placing them under a high or low working memory load. We hypothesized that occupying cognitive resources with a high working memory load would result in perceptual distortions of the risky prospect's reward magnitude and probability and thus lead to greater deviations from expected utility theory in both the gain and loss domains. Our empirical results were consistent with these predictions for choices in the gain domain, but not for the loss domain. We discuss potential reasons for this pattern of results, their implications for theories of decision-making under risk, and avenues for future research.

Introduction

For almost 300 years, people have been trying to explain deviations from linear probability and magnitude weighting as proposed by expected value theory (EVT). For example, expected utility theory (EUT) takes into account that to an individual, a gamble is not solely its expected value, but a subjective value, called utility (Starmer, 2000). According to EUT, subjects place such utilities on monetary outcomes and form their decisions accordingly. However, there is a huge body of empirical evidence (Bernoulli, 1738; von Neumann, 1944 or see Rabin, 2000; Schoemaker, 1982 for an overview) that suggests that people often choose outcomes that are not equal to the multiplication of subjective utility and the prospect's probability, and there is even less evidence that would support the linear relation proposed in EVT. In 1979, Kahneman and Tversky would then introduce the idea of separate reference dependence for the loss and gain domains with independent slopes, by claiming that decision-makers evaluate gains and losses differently in relation to the given context. This model – called Prospect Theory – argues that in average, people have utility functions that are concave over gains and convex over losses. The model thus incorporates the idea that people tend to be risk-averse towards gains and risk-seeking towards losses, but not without stressing the premise that loss looms larger than gains, symbolized by a steeper curve in the loss domain. However, even though Prospect Theory provided behavioral economics with a descriptive model that accounts for the puzzling deviations from linear decision models, they did not provide an explanation in the form of an underlying psychological mechanism for this phenomenon.

A recent model of decision-making under risk provided by Woodford and colleagues (2012; see also Khaw, 2017) proposes a way to fill this theoretical gap by incorporating the idea of noisy representations of monetary variables as a candidate mechanism. Their model explains the human tendency to avoid risk when evaluating prospects as a natural consequence of imprecise mental representations of the involved monetary magnitudes. Following this logic, increased mental noise through the strain of cognitive load should thus lead to decision-making with steeper loss and less steep gain functions compared to what is proposed in Prospect Theory. In other words, if working memory would indeed cause even noisier representations of magnitude, then we would expect to see more risk-aversion and less gambling in the gain domain and less risk-aversion and more gambling in the loss domain compared to subjects who find themselves in a state of little cognitive load. Our experiment therefore aspired to significantly advance a heated debate in the field by clarifying whether representational noise of monetary magnitudes can indeed account for the descriptive pattern provided by Prospect Theory.

Experimental procedures

22 male and 23 female individuals between the age of 19 and 36 (mean of 23 years) were selected randomly for a total of N = 55 and all participants provided informed consent as approved by the Research Ethics Committee of the Canton of Zurich. The participants were allocated to their seats and underwent a MATLAB-coded laboratory task (version R2015a, including PsychToolBox) where they would conduct an experiment in two stages: first a memory task and then a gambling task, whereas the gambling task incorporated the outcome of

the memory task. During the memory task, participants were shown a series of individual digits one at a time for 8 seconds. After having seen all digits, participants were asked to enter the entire series of numbers in the proper order into a text field provided on the screen. For this experiment, we used a dynamically adapting test that would present the participant with more difficult series (i.e. longer strings of digits) the better he or she performed. All participants started with five numbers and if they correctly recalled all five numbers in the right order, the program would show six digits for them to remember. This loop would be repeated until the subject recalled a series wrongly for two times or reached a capacity of nine digits[1]. The program would then take this number of digits to compute an individual's digit capacity, i.e. the maximum of digits they can remember. We decided for this adapting approach rather than a fixed number of digits across all subjects to ensure an individualized level of cognitive load in the subsequent gambling stage.

After the computer program estimated the subjects' working-memory capacities, it would enter the second stage, where participants were presented with a series of gambles (average number of gambles for each participant = 120). Half of these gambles required the participant to choose between two positive amounts (gains), the other half required them to choose between two negative amounts (losses). For each gamble, subjects would further choose between a risky option and a sure option. The sure option was always 15 CHF with 100% certainty. Depending on the domain (gain vs loss), which was randomly chosen yet equally distributed across all trials, this meant that subjects would either win or loose 15

[1] We chose a capacity of nine digits as the upper limit, since cognitive psychology suggests that the average memory capacity of human beings is seven. Having started with five digits (one standard deviation below the expected mean), for practical reasons, we decided to stop the first task once participants reach one standard deviation above the expected mean.

CHF for sure. The other prospect that was presented together with the 15 CHF would always have the same valence as the default option, but would offer a different amount than 15 CHF and an unsure probability in steps of 10 from 10% to 90%. The amounts of those risky options could vary between +20 and +35 CHF for the gain domain and between -10 and -20 CHF for the loss domain (for comparison, see Holt, 2002).

In summary, we used a dynamically adapting memory paradigm to ensure validity of our experiment and had participants choose between sure and risky options, for which we used equally many losses and gains over 120 trials. Naturally, a loss-gamble was accompanied by a loss-default and gain-gambles build pairs with gain-defaults. Subjects would thus repeatedly go through a loop in which they are first presented with a digit span at the onset of a loop, then make four to eight gambling decisions and are then asked to enter the previously shown digits in a text field on the screen. These spans were either presented in a low load or a high load condition, whereas the number of digits in the high load condition was equal to the participant's digit capacity estimated during the memory stage of the experiment (usually 6 to 8 digits). We intended the high load condition to be cognitively exhausting for participants, whereas the low load condition (2-3 digits) should be rather easy to solve.

After the subjects entered the digit span in the provided text field, the program would immediately present a new series of digits, which was presented under either a high load or low load condition, again random for the individual trial, but equally distributed across all trials. In total, every subject would thus go through 30 digit-gambling blocks, after which they were informed about the experiment being over and payments being made.

During the standardized introduction before the experiment, participants were incentivized to perform well by informing them that every correctly remembered digit span would add 1 CHF to their total balance that started with 10 CHF show-up fee. At the end of the study, the program would further randomly choose one decision in the gain domain and one decision in the loss domain and add them to the total balance. Naturally, the nature of the prospect (sure vs. risky) would be relevant here. For example, let's assume a participant had been offered a gamble between a prospect of 26 CHF with 40% and the default option of 15 CHF with 100% and another gamble between a prospect of -20 CHF for 60% and the default option of -15 CHF with 100%. In the first scenario, the participant decided for the risky option (26 CHF with 40%) and in the second scenario for the sure option (-15 CHF with 100%). Let's further assume the participant recalled 9 of the 15 digit spans correctly. He or she would thus have a balance of 19 CHF before adding the two prospects. With a probability of 40%, this subject would receive 26 additional CHF and lose 15 CHF for sure, what would end up in a total amount of 30 CHF that would be paid to the subject directly. However, in 60% of the cases, the subject would receive 0 CHF from the risky option and still lose the 15 CHF from the sure default option. This would bring his or her balance down to 4 CHF. Participants were clearly and transparently informed about this way of calculating their outcome at the beginning of the experiment and were also given the chance to ask questions for clarification. When presenting this information, we furthermore ensured to avoid any framing that would result in subjects becoming biased towards risk-avoiding or risk-seeking preferences (Tversky, 1981).

Results

N = 6309 trials completed by the 55 participants of the study were included into the analysis. To ensure data quality, it was first tested whether subjects' working memory capacities operated as a confound variable for their gamble decision-making. A second analysis was then conducted to observe whether the gambles' magnitude and probability had a significant effect on choices. Finally, we tested our hypothesis that subjects in the high load condition choose the risky option more often in the negative and less often in the positive domain compared to people in low load conditions. An alpha level of 0.05 was used for all statistical tests.

Preliminary Analyses

To find out whether subjects' trait capacity affected gambling behavior, three one-way between-subjects ANOVAs were conducted. We expected to find non-significant results for the high load condition, since we tailored the load to each individual's capacity and thus theoretically excluded differences in working memory capacity as a confound. However, in the low load condition, individuals with higher capacity might be able to represent magnitudes and probabilities more accurately than people with a rather inhibited ability to handle numbers, and thus make choices that are more aligned with the expected value of the prospects. Finding non-significant results for those analyses would therefore allow to exclude working memory capacity as a confound variable for the risky behavior pattern found under cognitive load.

The first ANOVA was carried out on all trials of the experiment, regardless of whether they were decided upon in the loss or gain domain. Congruent with our expectations, there was no significant effect between subjects' capacities and the decision to gamble or not ($F = 3.484$, $p = 0.62$). The second ANOVA focused solely on the trials in the gain domain, and there was no significant effect of the capacities on the decision to gamble as well ($F = 0.041$, $p = 0.839$). The last ANOVA was conducted for the trials in the loss domain only and again, individual capacities did not show a significant effect on decisions ($F = 3.132$, $p = 0.0768$). For detailed information consult table 1.

In congruence with past literature on behavioral economics (for example, see Starmer, 2000), we further expected to find that subjects' willingness to decide for a risky prospect increases as a function of the prospect's magnitude and valence across both domains, which is to say that the prospect's expected value significantly predicts choices across both domains. We thus conducted another one-way ANOVA and indeed found a highly significant effect ($F = 122.7$, $p = 0.000$***). For specific values consult table 2.

Converging the results of our four ANOVAs (three that analyzed the influence of capacity on risk-taking and one that observed the influence of a prospect's expected value on risk-taking), it can be assumed that basic data quality is granted and that we can test our hypothesis with the current dataset.

Hypothesis

Given the complex data structure of the experiment (a categorical dependent variable with individualized, yet nested independent variables), we tested our hypothesis with two generalized linear mixed models; one for the gain domain and one for the loss domain. All betas, standard errors, z-values and p-values of the fixed effects are listed in table 3. To examine the relation of cognitive load and risk-taking across all trials, we computed the following logistic regression:

$$R_{i1} = \beta_0 + \beta_1 * high\_load + \beta_2 * risk\_amount + \beta_3 * risk\_probability + \beta_{IA1} * risk\_amount * risk\_probability + \beta_{IA2} * risk\_probability * high\_load + \beta_{IA3} * risk\_amount * high\_load + \beta_{IA4} * risk\_probability * risk\_amount * high\_load + \varepsilon$$

in which R is a binary choice vector taking the value of 1 whenever the risky option is selected and 0 otherwise. We used the same regression for both the gain and loss domain. Indeed, we find that the interaction between high load, probability of winning and the amount to win in the gain domain showed a significant effect on subjects' choice (β = -10.87, *SE* = 5.22, z =-2.08, p = 0.04). This result partly supports our hypothesis, but seeing that there was no significant interaction between high load, probability and magnitude in the loss domain (β = 1.26, *SE* = 3.51, z =0.36, p = 0.72), our hypothesis is not fully supported by the present data.

The interaction between high load and the probability of winning a certain amount is illustrated in figure 1. For comparison, the same interaction in the loss domain is illustrated in figure 2. There was no significant effect between the amount in the gambling option and the high load in both domains. The random effects of the two generalized linear mixed models are reported in table 4.

Table 1

Analysis of Variance (ANOVA) between capacity and gamble in different conditions

	df	*η*	*F*	*p*
Gamble	1	0.000	3.484	0.062
Gamble in gain domain	1	0.000	0.041	0.839
Gamble in loss domain	1	0.000	5.136	0.076

Note. N =6309. All numbers were rounded to the third decimal position. *** $p = 0$, ** $p \leq 0.001$, * $p \leq 0.01$.

Table 2

Analysis of Variance (ANOVA) between the interaction between probability and amount and gamble

	df	*η*	*F*	*p*
Probability and amount	1	0.019	122.7	0.000***

Note. N = 6309. All numbers were rounded to the third decimal position. *** $p = 0$, ** $p \leq 0.001$, * $p \leq 0.01$

Table 3

Fixed effects in gain domain and loss domain from the mixed-effects regression specified in equation 1.

	β	*SE*	*z*	*p*	
Gain domain					
(Intercept)	-13.53	2.27	-5.95	0.00	***
High Load	-5.37	3.09	-1.74	0.08	
Amount of risky option	3.81	2.03	1.88	0.06	
Probability of risky option	12.89	3.16	4.09	0.00	***
Interaction between amount and probability of risky option	2.98	3.25	0.92	0.36	
Interaction between amount of risky option and high load	5.90	3.28	1.80	0.71	
Interaction between probability of risky option and high load	9.49	4.77	1.99	0.05	*
Interaction between amount and probability of risky option, and high load	-10.87	5.22	-2.08	0.04	*
Loss Domain					
(Intercept)	5.18	1.79	2.90	0.00	**
High Load	-3.92	2.33	-1.69	0.09	
Amount of risky option	1.08	1.49	0.73	0.47	***
Probability of risky option	11.40	3.39	3.36	0.00	***
Interaction between amount and probability of risky option	12.97	3.04	4.27	0.00	***
Interaction between amount of risky option and high load	-3.13	2.01	-1.56	0.12	
Interaction between probability of risky option and high load	1.61	4.09	0.39	0.69	
Interaction between amount and probability of risky option, and high load	1.26	3.51	0.36	0.72	

Note. n = 3509 trials in the gain domain and n = 2800 trials in the loss domain. Random intercepts and slopes for all fixed effects regressors were included for each of the 55 participants in our dataset. All numbers were rounded to the second position after decimal point. *** $p = 0$, ** $p \leq 0.001$, * $p \leq 0.01$

Table 4
Random effects in gain domain and loss domain

	σ^2	SD
Gain domain		
(Intercept)	103.49	10.17
High Load	122.22	11.06
Amount of risky option	27.45	5.24
Probability of risky option	119.84	10.95
Interaction between amount and probability of risky option	65.05	8.07
Interaction between amount of risky option and high load	128.99	11.36
Interaction between probability of risky option and high load	295.66	17.20
Interaction between amount and probability of risky option and high load	346.53	18.62
Loss Domain		
(Intercept)	7.86	2.80
High Load	3.86	1.97
Amount of risky option	2.60	1.61
Probability of risky option	127.66	11.30
Interaction between amount and probability of risky option	136.57	11.69
Interaction between amount of risky option and high load	2.98	1.70
Interaction between probability of risky option and high load	33.13	5.76
Interaction between amount and probability of risky option and high load	22.99	4.80

Note. n = 3509 trials in the gain domain and n = 2800 trials in de loss domain. 55 Subjects observed. All numbers were rounded to the second position after decimal point. *** $p = 0$, ** $p \leq 0.001$, * $p \leq 0.01$

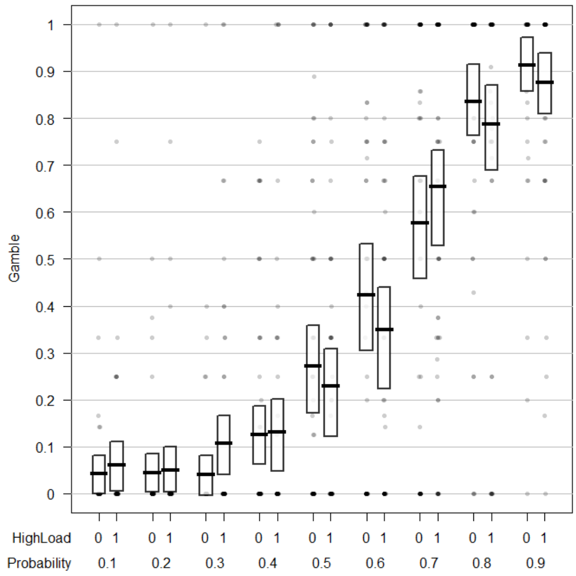

Figure 1. Gambling by cognitive load and probability of winning a certain amount

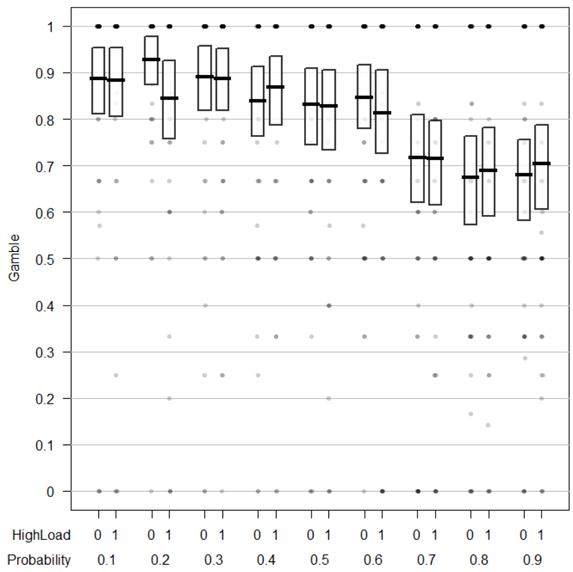

Figure 2. Gambling by cognitive load and probability of losing a certain amount

Discussion

Our findings indicate that an individual's behavior in situations of risk is, in addition to being dependent on a gamble's magnitude and probability, a function of the risk's nature (gain vs. loss) and the degree of cognitive load the individual experiences. However, since we found different effects for the loss and gain domains, the present data can only partially support our hypothesis and the noisy representation theory of Woodford and colleagues. Whilst it is true that for gains, people become more risk-averse and settle more frequently for sure options, decisions in the loss domain still show the same degree of risk-seeking as it is found for regular samples (Kahneman and Tversky, 1979). Our results are therefore inconsistent with the specific predictions of the noisy representation theory, but we find that gain domain choices under high load are less consistent with the expected value of gambles than it would be predicted by Prospect Theory. This could be caused by a noisier representation of reward magnitudes and a subsequently decreasing precision with which people can represent decision variables such as magnitude and probability. The experience of cognitive load might thus lead to decision-making less in accordance with expected value strategies for the gain domain.

One possible explanation for why we found different effects for the gain and loss domains is that the working memory load paradigm does not sufficiently constrain participants' mental capabilities and therefore does not compete with the representation of magnitudes and probabilities enough. Future studies are thus encouraged to reproduce the current study with different paradigms that impose cognitive load on participants, such as sensory irritation (e.g. flashing lights, loud noises or irritating odors that distract people from focusing on the gambles) or deprivation of sleep (Mullette-Gillmann, 2015). Alternatively, researchers could also implement working memory tasks that demand not only numerical domains, but also figural and verbal ones.

Another potential explanation for the separate effects is a commonly reported problem across different studies of risk – which is, in fact, the operationalization of losses itself. By their nature, studies are usually not able to inflict real monetary losses upon participants, since it would be hard to find people willing to come into a laboratory, undergo a time-consuming experiment and then leave with even less money than they initially had. For scientific experiments, subjects are thus paid a guaranteed amount for participation and are incentivized to participate in behavioral economics experiments by having a solid chance to win additional money. In the end, researchers are obliged to pay for their participants' time and until a better paradigm is found, this will continue to be a pressuring problem for behavioral economics and the science of risk-preferences, especially when it comes to studying losses. It is thus possible that participants may have represented losses in our study as *earning less*, rather than a *negative outcome*. Knowing that they will return home with more money than they came with in any case might have made them gamble as if they were confronted with gains only, when we wanted them to decide between either of two loss prospects.

However, there are not only methodological, but also theoretical arguments as to why we did not find the same effects for both the loss and the gain domain. An alternative explanation for our data is that people in the gain domain showed a stronger shift to heuristic strategies than people in the loss domain. In other words, when having to choose between a prospect that wins a subject a certain amount for sure and a prospect that wins an amount that is larger, but is only won stochastically, subjects use the certainty of the prospect as a heuristic for their decisions and they do so significantly more frequent when they are under high cognitive load. This approach is congruent with past literature on how demands of cognitive resources drive heuristic decision-making (Shah, 2008; Payne, 1976). It thus seems reasonable to assume that for gains, being in a condition of cognitive load leads to heuristic decision-making that is focused on the certainty or non-certainty of two prospects, rather than their specific monetary amounts or values. For losses however, we find that people are not affected by the cognitive load and instead show the same pattern of decision-making as proposed in Prospect Theory, without having a steeper curve.

What might help to explain this difference is a wide body of literature suggesting that the human brain regards losing something and gaining something as two separate dimensions that trigger different mental mechanisms instead of being opposite pols on a continuum. These findings reach across a huge variety of domains, in which "positive" (gaining money, being happy) and "negative" (experiencing the threat of a loss, feeling pain or sadness) events are associated with two distinct paths of cognitive reactions. For example, Schwarz (1983) found that experiencing a positive mood results in people using more heuristic thinking when evaluating their environment, whereas experiencing a negative mood such as sadness results in more analytical and vigilant thinking. Fundamentally for prospect theory, Tversky (1981) further found that adding a gain or loss frame to an otherwise identical scenario changes the way people react to it. And even on the sensomotoric level, it has been found that there is an exponentially higher reaction to pain (i.e. an event coded with a negative value in the brain) than to other stimuli (Gescheider, 1997; Kacelnik, 1998). It is also found that negative spillover effects between life domains last longer than positive spillovers (Sonnentag, 2013) and that the loss of resources causes exponentially more stress for an individual than the gaining of resources causes pleasant feelings (Hobfoll, 1989; Hobfoll, 2002). Finally, there are neurobiological findings that suggest that the human brain possesses two different systems to deal with either situations where a negative stimulus should be avoided or situations where a positive stimulus should be approached (Gray, 1970; Gray, 1987; Carver 1994). Converging these findings, the natural reaction of human beings to aversive situations seems to be the attempt of avoiding (further) loss and thus processing information slowly, analytically and vigilantly, whereas the reaction to positive situations is approaching behavior and more heuristic decision-making (Petty and Cacioppo, 1986). Also from an evolutionary perspective, not gaining something (i.e. a new friend or additional resources) is fundamentally less problematic than losing something (i.e. a long-hold friend or one's life). This perspective suggests that gaining additional money is less important to people than losing money they already have (McDermott, 2008).

This difference in how positive and negative events are treated could explain our different findings for gain and loss behavior under cognitive load insofar as that the presence of a loss (i.e. an intermediate threat for personal resources such as the accumulated money in our experiment) acts as an environmental signal that inhibits participants from using heuristics in their decision-making more than if the environment does not signal such a threat. Thus, when facing situations of cognitive load, those different styles of information processing lead to participants being more or less attentive to their decisions.

Observing that a subject's working memory capacity trait has no influence on preferences across both domains, we further controlled for a potential confound of our findings with IQ and memory abilities (Shah, 2005). This confound can further be excluded as an explanation because of the individualized experimental design used in the study that assures that every participant experiences a sufficiently high cognitive load.

In other words, no matter how good a subject is at remembering and dealing with numbers, they show the same pattern of using certainty as a heuristic for decision-making in the gain domain. It is therefore reasonable to assume that our findings cannot be simply explained by an affinity for numbers and an increased ability to handle abstract entities like probabilities. Instead, it is the state of being cognitively loaded that leads subjects to settle for sure monetary options when they are presented with two potential gains. Yet for losses, even people with lower working memory capacity allocate their mental resources to examine the loss prospect more carefully than their equivalents in the gain domain.

We therefore speculate that it is this difference in importance and attention assigned to the gain and loss trials that caused people to behave differently in the gambling scenarios, depending on whether the algebraic sign of the gamble was positive or negative. To use Kahneman's (2011) terminology, one might say that for gains, people in situations of cognitive load are making decisions based more on the automatic, heuristic and "fast" *System I*, whereas for losses, people also apply a heuristic of the prospect's valence, but they do so less automatic due to an increased degree of attention.

Conclusions

The present study finds that for situations of financial risk, people's decision-making is a function of the prospect's valence, its magnitude, its probability and the degree of cognitive load an individual experiences. This interaction is mediated by differences in allocation of attention that happens for gains and losses. In case of a positive valence, people are more likely to settle for sure and safe options, rather than risky options of higher magnitude. In other words, cognitive load makes people averse to gambling when it comes to resources they could win. However, if there are resources that could be lost, participants deploy more attentive resources and use less heuristic processing, which is why the additional cognitive load does not alter their decision-making. We therefore conclude that with respect to our data, noisy representation theory cannot explain the risk-behavior pattern described in Prospect Theory sufficiently. Integrating those results with future and potentially significant effects found with different methodologies might advance the field of behavioral economics substantially by understanding the psychological processes underlying the widely applied Prospect Theory better.

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