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The Relationship between Adaptive Strategy Selection and Cognitive Effort: An Eye-tracking Study*

Adaptacyjna selekcja strategii decyzyjnych a wysiłek poznawczy. Badanie okulograficzne

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Abstract:

We investigated whether people make choices and regulate cognitive effort adaptively depending on the task structure. We employed an eye-tracking methodology to examine whether measures of cognitive effort (i.e., reaction times and pupil size) predict choices in high and low expected values ratio choice problems. We measured how frequently participants made choices consistent with predictions of cumulative prospect theory vs. priority heuristic models. Participants were more likely to make choices predicted by cumulative prospect theory in choice problems with high expected value ratio, while in choices of low expected value ratio problems, they tended to select an alternative predicted by priority heuristic. Choice latency but not pupil size was directly related to choices contingent upon cumulative prospect theory. Notably, we observed that the likelihood of choices consistent with priority heuristic decreased with pupil size, but only in case of choice problems with low expected value ratio.

Keywords: adaptive strategy selection, risky choice, eye-tracking, pupil size, cognitive effort.

Streszczenie:

W badaniu okulograficznym sprawdzaliśmy, czy struktura problemu decyzyjnego oraz zaangażowanie poznawcze będą przewidywały wybory w warunkach ryzyka. Wykorzystaliśmy problemy decyzyjne o niskiej i wysokiej proporcji wartości oczekiwanych, która to miara może być wskaźnikiem trudności obliczeniowej lub wagi problemu decyzyjnego. Jako wskaźniki zaangażowania poznawczego zastosowaliśmy miary wielkości źrenicy oraz czasu reakcji. Sprawdzaliśmy, jak często wybory były zgodne z przewidywaniami teorii perspektywy oraz heurystyki pierwszeństwa. Wyniki

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wykazały, że struktura problemu decyzyjnego nie przewidywała zmiany w wielkości źrenicy. Osoby badane częściej podejmowały decyzje zgodne z przewidywaniami teorii perspektywy w problemach o wysokiej proporcji wartości oczekiwanych. W problemach o niskiej proporcji wartości oczekiwanych wybory były częściej przewidywane przez heurystykę pierwszeństwa. Struktura problemu decyzyjnego nie wpływała na zmiany wielkości źrenicy, ale badani dłużej dokonywali wyborów zgodnych z przewidywaniami teorii perspektywy. Ponadto zaobserwowaliśmy, że prawdopodobieństwo wyboru zgodnego z przewidywaniami heurystyki pierwszeństwa zmniejszało się wraz z szerokością źrenicy, ale tylko w problemach decyzyjnych o niskiej proporcji wartości oczekiwanych.

Słowa kluczowe: adaptacyjne podejmowanie decyzji, wybory ryzykowne, okulografia, zmiany wielkości źrenic, wysiłek poznawczy.

1. Introduction

Decision making under risk is often considered as a tradeoff between accuracy and effort (Payne, Bettman, 2004). That is, people aim at maximising the accuracy of their decision (they intend to make the best of possible choices, which satisfies their goals), but at the same time, they want to minimise cognitive effort engaged in information processing. This is especially apparent in a complex decision environment, in which scant cognitive resources are confronted with task demands. Under such conditions, people are able to adaptively select and employ a constrained repertoire of choice strategies for solving a choice problem (Payne, Bettman, Johnson, 1993). Since the selection of strategies is contingent upon a choice problem structure (e.g., its difficulty), different choice strategies require different amounts of cognitive effort (Payne, Bettman, Johnson, 1988). In the current study, we tested whether a choice problem structure influences the selection of strategies, and whether cognitive effort (measured by pupil size), as well as deliberation (measured by choice latency), predict choices consistent with the expectation or heuristic models of risky choice.

Choice strategies differ in their computational complexity and therefore require different amounts of cognitive resources to be efficiently applied. For example, normative compensatory strategy (e.g., WADD) involves more comprehensive alternative-wise information search and more complex multiplying/adding operations, in comparison to a faster and simpler non-compensatory lexicographic strategy that involves straightforward attribute-wise comparisons (Payne *et al.*, 1988). In case of decision making under risk and uncertainty, models of choice can be categorised into two main families. Expectation models such as expected value (EV), expected utility (EU; Bernoulli, 1954), and their other non-linear variants, including cumulative prospect theory (CPT; Tversky, Kahneman, 1992), assume that a decision maker makes tradeoffs, weighting the (subjective) value of outcomes by (subjective) representation of their probabilities (i.e., decision weights). As a result of these mental transformations, a decision maker should choose an alternative with the highest utility – a subjective measure of "value" (Starmer, 2000). In contrast, heuristic models, such as the priority heuristic (PH; Brandstätter, Gigerenzer, Hertwig, 2006), are simplified procedures that ignore some information and, without tradeoffs, allow a person to make a satisfactory choice, saving time and limited cognitive resources (Simon, 1955). Cognitive operations within expectation models seem to be more complex and effortful compared to heuristic models. While the former involve processing all information about a choice problem, the latter are based on a limited search and are highly selective in terms of

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processed information. Hence, we expect that employing cognitive operations predicted by either expectation or heuristic models will be associated with differences in mental effort and time spent on deliberating on a choice problem. To address this research problem, we conducted an eye-tracking study in which we collected and analysed standard process-tracing measures: pupil size and choice latency. While the former has been shown to reflect mental effort[1] required to process information (Kahneman, Beatty, 1966; Wang, 2011), the latter is indicative of how much deliberation is involved in solving a choice problem (Ghazal, Cokely, Garcia-Retamero, 2014; Petrova, Garcia-Retamero, Catena, van der Pligt, 2016; Petrova, Traczyk, Garcia-Retamero, 2019).

According to the Simon's idea of bounded rationality, "human rational behaviour (and the rational behaviour of all physical symbol systems) is shaped by scissors whose two blades are the structure of task environments and the computational capabilities of the actor" (Simon, 1990, p. 7). In light of these words, the selection of appropriate choice strategy is driven by the cognitive ability to use a particular strategy, but also it is contingent on the task structure and decision environment, which has been extensively documented in literature (Gigerenzer, Goldstein, 1996; Gigerenzer, Todd, ABC Research Group, 1999; Payne *et al*., 1993).

For instance, in reference to the above-mentioned differentiation between the expectation and heuristic models, Brandstätter *et al*. (2006) demonstrated that in simple monetary lotteries, the heuristic strategy (PH) predicted choices better than expectation models (CPT/EV), but the structure of the task moderated this effect. In particular, PH performed better when the ratio between gambles' EVs was low, but it made worse predictions when the ratio between gambles' EVs was high. In such environment, CPT/EV was more correct in predicting risky choices. More recently, this problem was investigated in detail by Pachur, Hertwig, Gigerenzer and Brandstätter (2013). The authors conducted a quantitative model comparison focusing on process predictions posited by the two prominent models of risky choice – CPT vs. PH. They presented participants with a set of 48 binary two-outcome choice problems (framed as gains and losses). The choice problems were constructed such that choosing one of two gambles was always predicted by CPT/EV or PH models. Additionally, the problems differed in computational difficulty, operationalised as the ratio between gambles' EVs. That is, easy problems were defined as those having an EV ratio of between 5 and 6, whereas difficult problems were defined as those having EV ratio around 1. In this sense, making a choice that maximises EV in high EV ratio problems appears to be easier, because the difference in EVs is substantial at hand. Contrarily, in low EV ratio problems, a choice is computationally more demanding because negligible differences in EVs involve accurate and exhaustive processing of all parameters describing gambles. The results demonstrate that the structure of choice problems trigger distinct strategies: in low EV ratio problems individual choices were consistent with predictions of PH, while high EV ratio problems were better predicted by CPT/EV.

In a similar vein, Traczyk *et al*. (2018) used the same set of choice problems (only gain domain) to replicate this effect. They corroborated previous results, demonstrating that the ratio between gambles' EVs led to choices consistent

[1] Pupil size is also interpreted as an indicator of emotional arousal (Bradley, Miccoli, Escrig, Lang, 2008).

with CPT/EV or PH. Importantly, objective numeracy (i.e., an ability to understand and use statistical and probability information) played a crucial role in this relationship. Participants with high objective numeracy, in comparison to participants with low numeracy, were more likely to adaptively selected choice strategies. In the case of high EV ratio problems, they tended to maximise EV, and their choices were consistent with CPT/EV predictions. In low EV ratio problems, people with high numeracy switched to heuristic processing – their choices were better predicted by PH. In the case of people with low numeracy, the tendency to adaptively select choice strategy was not so pronounced – participants with low numeracy made choices predicted by either CPT/EV or PH depending on EV ratio, but their flexibility in using different choice strategies was lower in comparison to more numerate participants. The authors argued that high EV ratio problems can be understood as being more meaningful because selecting a gamble with higher EV would result in a higher payoff. In contrast, low EV ratio problems can be understood as being more trivial because choosing the normatively better gamble with higher EV would not result in a substantially larger payoff. This could suggest that mental effort related to specific information processing implied by expectation or heuristic models (i.e., CPT/EV vs. PH) might depend on the ratio between EVs.

Cognitive effort engaged in decision-making processes might be investigated by recording task-evoked changes in the pupil, which is a widely-used process-tracing measure (Wang, 2011). For instance, it has been demonstrated that pupil size predicted an increase of the decision threshold in difficult conflict decisions (Cavanagh, Wiecki, Kochar, Frank, 2014). Additionally, pupil size was sensitive to negative outcomes (Hochman, Yechiam, 2011), was greater in case of a more demanding pricing task in comparison to a rating task (Rubaltelli, Dickert, Slovic, 2012), decreased with absolute differences in gambles' EVs when the gambles were presented in the description, but not experience, condition (Glöckner, Fiedler, Hochman, Ayal, Hilbig, 2012), and increased with mean EV of gambles (Fiedler, Glöckner, 2012). In the present study, we add to these findings. In particular, we used pupil size as a measure of cognitive effort to predict strategy selection in risky decision problems.

To summarise, in the present study we investigated whether the structure of choice problems would influence strategy selection and risky decision making. Specifically, in an eye-tracker study, we adapted a set of high and low EV ratio choice problems used in previous studies (Pachur *et al.*, 2013; Traczyk, Sobkow *et al.*, 2018). We hypothesised that the ratio between gambles' EVs would lead to choices predicted by different models (i.e., CPT/EV in high EV ratio vs. PH in low EV ratio problems). Moreover, we explored whether process-tracing measures of mental effort and deliberation would predict choices. We expected that higher mental effort (measured by pupil size) and longer deliberation (measured by choice latency) would be related to using a more effortful choice strategy (i.e., CPT/EV). Additionally, we tested whether the EV ratio moderated this relationship.

2. Method

2.1. Participants

Twenty-one adult volunteers recruited from the undergraduate student population took part in the study. Participants gave consent to take part in the study after the researcher had provided all necessary information regarding the procedure.

2.2. Materials and Procedure

We employed 24 binary choice problems consisting of two-outcome gambles taken from Pachur *et al.* (2013). We used only problems in gain domain. Half of the decision problems were high EV ratio problems (mean EV ratio of 5.86, *SD* = 0.024) and the other half low EV ratio problems (mean EV ratio of 1.06, *SD* = 0,005). These gambles had two main characteristics. Firstly, the ratios of the gambles' EVs were between either 1 and 2 or 5 and 6. Secondly, PH (Brandstätter, Gigerenzer, Hertwig, 2006) and CPT with standard parameters (Tversky, Kahneman, 1992) always predicted the opposite choices. Additionally, CPT and EV models made the same predictions for choices (Pachur *et al.*, 2013). CPT assumes that decision makers behave as if they computed the overall value of a gamble multiplying subjectively transformed outcomes and their weighted probabilities and choose a gamble with a higher value. In contrast, PH predicts that decisions are guided by priority and stopping rules. Priority rule implies that minimum gains, probabilities of minimum gains, and maximum gains are considered in the fixed order. The inspection is stopped resulting in a choice when the difference between minimum (maximum) gains is larger than 10% of the minimum (maximum) gain, or if the difference in probabilities of minimum gains is larger than 10% of the probability scale. In this sense, CPT assumes trade-offs between outcomes and probabilities and evaluation of risky prospects in separate, while PH assumes comparative evaluation based on a limited number of information and without trade-offs. To illustrate, in a choice problem: A (5.40, 0.29; 0, 0.71) vs. B (9.70, 0.17; 0, 0.83), PH predicts the choice of gamble A because of the probability of minimum outcome, while CPT (with the original parameter set from Tversky, Kahneman, 1992) predicts the choice of gamble B because of the higher subjective value (1.3805 vs. 1.7802; see Appendix for a list of all decision problems used in the study and predictions of CPT/EV and PH).

Twenty-four decision problems were displayed in random order. To control for order effects, nine of these problems were repeated twice with the changed side of the screen. We asked participants to choose the gamble they preferred. Each trial started with blank screen (1–2 s), followed by a fixation cross (with randomly sampled latency from 1 to 2 seconds sampled) to direct attention to the center of the screen. All information was displayed at equal distance from the initial fixation point. Additionally, we used a monospaced black-colored Courier typeface displayed on a gray background. As a result, every character had the same width and each piece of information (probabilities and outcomes) equally filled the space of the display. The mean luminance of low and high EV ratio choice problems were identical. We used Cedrus Response Pad RB-540 to facilitate choice without the need to glance at keyboard. The left (right) gamble was selected by pressing a key on the left-hand (right-hand) side of the response pad. Gaze data were registered using the eye gaze binocular system (Remote Eyetracking Device by SensoMotoric Instruments SMI, Teltow, Germany) with a sampling rate of 120 Hz and an accuracy of approximately 0.45°. Stimuli were presented on a 475 x 300 mm monitor (resolution = 1024 x 768). We designed the experiment using Experiment Center software (Version 3.4; SensoMotoric Instruments). Gaze data were recorded by iView X 2.7 software, following five-point calibration plus validation (average tracking ratio = 94.93%). In order to avoid distortions in the pupillary response measurement due to direct light on the tracker and participants' eyes, we conducted the experiment in a dimmed room with constant luminance conditions for all participants.

3. Results

3.1. Predictions of the Priority Heuristic and Expectation Models (CPT/EV)

In low EV ratio problems, the PH model predicted choices better than CPT/EV, 76% (*SE* = = 2.7), and the predictions of this strategy were significantly better than chance (50%), $\chi^2(1)$ = = 68.1, $p < 0.001$. In contrast, CPT/EV models predicted choices better in high EV ratio problems, 57% (*SE* = 3.1), which also significantly differed from a chance level, $\chi^2(1) = 5.43$, p = = 0.019 (Figure 1). The results were extended by McNemar's *chi* squared test, $\chi^2(1) = 6.28$, p = = 0.01, thus there is considerable difference between high and low EV ratio problems in proportion of choices contingent upon CPT or PH. The paired sample *t*-test showed similar results, $t(20) = 4.90$, $p < 0.001$, $d_z = 1.4$ (Lakens, 2013). In high EV ratio problems, participants applied strategies that were consistent with predictions of expectation models. In contrast, in low EV ratio problems, PH was participants' major strategy (see Appendix for information about the proportion of choices contingent upon CPT/EV strategy per each of the decision problems). Additionally, we examined the consistency of choices in repeated pairs of choice problems. Paired *t*-test revealed that in the low EV ratio problems choices were less consistent than in the high EV ratio condition, $t(20) = 3.35$, $p < 0.01$, $d_z = 0.73$.

3.2. How do Cognitive Effort Measures (Pupil Size, Time) Predict Choice?

We applied a subtractive baseline correction of pupil (Mathôt, Fabius, van Heusden, Van der Stigchel, 2018). Then, we removed observations up to 220 ms from stimulus onset due to delayed

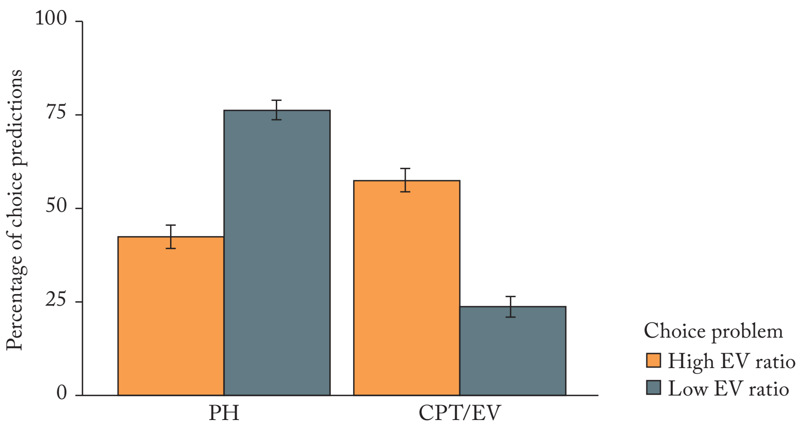

Figure 1. Predictions for Individual Choices as a Function of Choice Problem (High vs. Low EV Ratio). The Error Bars Represent Standard Error of the Proportion

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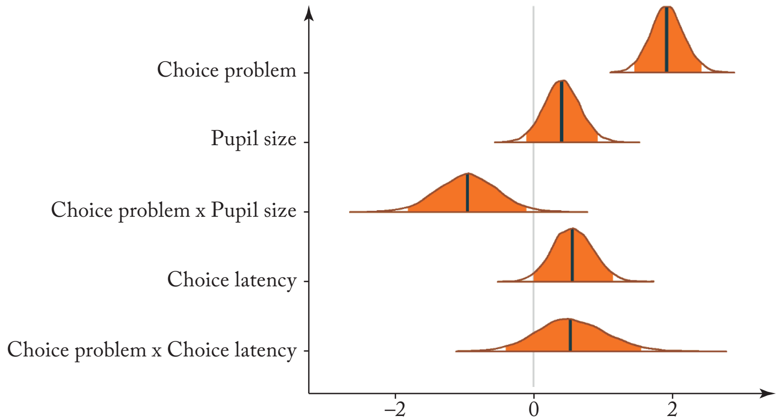

Figure 2. Distributions of Slopes from a Model Predicting CPT/EV vs. PH Choice. Shaded Areas Represent 95% Credible Intervals under Estimated Posterior Density Curve. Estimates Are on Logit Scale

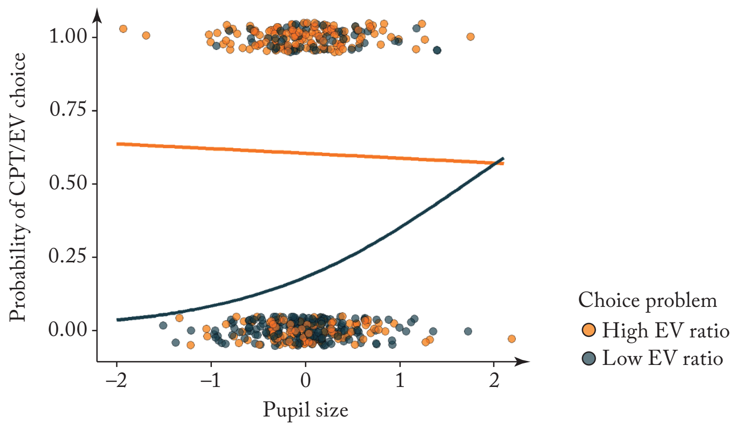

Figure 3. The Probability of Choice Consistent with CPT/EV as a Function of Pupil Size and the Choice Problems' EV Ratio. Pupil Size Was Centered and Standardised Dividing by Two SDs. The Lower the Probability of CPT/EV Choice, the Higher the Probability of PH Choice

pupillary response caused by slow iris muscle constriction (Mathôt, Van der Stigchel, 2015; Salthouse, Ellis, Diener, Somberg, 1981). We grouped data per each subject and each gamble applying median of pupil size per each choice problem. We used a multilevel approach in the Bayesian Generalised Linear Models framework via Stan (Barr, 2008; Stan Development Team, 2018). Weakly informative priors were employed, which perform moderate regularisation, and stabilise computation. We fitted a multilevel model that predicted choice (contingent on CPT/EV vs. PH, coded as 1 and 0, respectively) with the choice problem (low vs. high EV ratio, coded as –0.5 and 0.5), pupil size, choice latency from stimuli onset to response with varying intercepts for each participant. For the sake of better interpretation of regression coefficients,

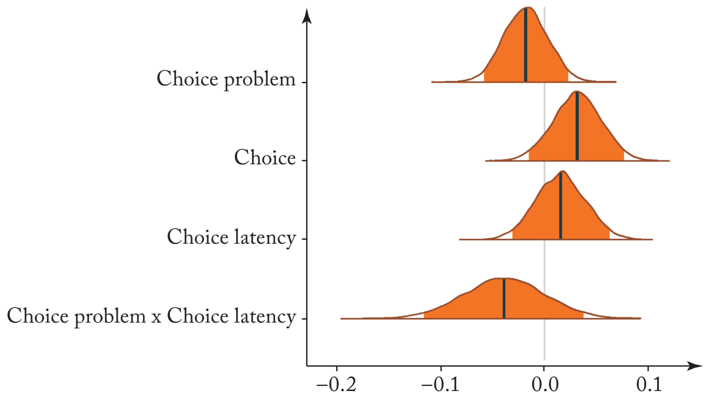

Figure 4. Distributions of Slopes from Model Predicting Pupil Size. Shaded Areas Represent 95% Credible Intervals under Estimated Posterior Density Curve. Estimates Are on Logit Scale

Table 1. Coefficients of Variables from Models which Predicted Choice and Pupil Size

Variable	Median	2.5%	97.5%	Rhat
Choice				
Intercept	−0.531	−1.094	0.021	1.0
Choice problem	1.923	1.464	2.397	1.0
Pupil size	0.408	−0.092	0.916	1.0
Choice problem x pupil size	−0.966	−1.842	−0.103	1.0
Choice latency	0.552	−0.003	1.141	1.0
Choice problem x choice latency	0.534	−0.393	1.531	1.0
Pupil size				
Intercept	−0.065	−0.132	0.007	1.0
Choice problem	−0.018	−0.058	0.023	1.0
Choice	0.031	−0.015	0.076	1.0
Time	0.016	−0.031	0.062	1.0
Time x choice problem	−0.039	−0.116	0.038	1.0

Note: Two level categorical variable *Choice problem* was coded as follows: 0.5 – high EV ratio problems, −0.5 – low EV ratio problems.

we standardised numeric inputs (pupil size and time) by centering and dividing them by two standard deviations (Gelman, 2008). We ran 4,000 iterations of model fitting in four chains. Diagnostics did not show any problems with Markov chains: each RHat indicator is almost 1 (Gelman, Lee, 2015).

We found strong evidence for the choice problem effect on choice (Figure 2). In high EV ratio problems, choices were consistent with CPT/EV models to a greater extent. As we showed earlier, this pattern was inversed in low EV ratio problems. Among other effects included in our study, the effect of the choice problem on choice was the strongest. Pupil size was not a credible predictor of choice. Notably, we observed that the relationship of pupil size and choice was moderated by the choice problem: the probability of choice consistent with the predictions of CPT/EV increased with pupil size, but only in low EV ratio problems (Figure 3). Moreover, latency was a credible predictor of choice, since its slope was larger than zero with roughly 97% probability: participants made choices predicted by CPT/EV slower than these predicted by PH. We did not observe any interaction effect of choice latency and choice problem.

Finally, we fitted multilevel model with pupil size as a response variable following the same rationale as in the previous model. That is, we regressed pupil size on choice, choice latency, and choice problem adding adjustments which come from varying intercept for each participant. Conditional on the data and the model, we concluded that we have no foundation to believe in any of the effects of choice, latency or problem on pupil size (Figure 4). Exact values of coefficients from models which included predictions of choice and pupil size are in Table 1.

4. Discussion

In the current eye-tracking study, we used a set of high and low EV ratio risky choice problems to investigate an impact of the problem structure on strategy selection, as well as the role of mental effort and time in this effect. We found that participants were more likely to make choices consistent with predictions of the expectation models (CPT/EV) when EV ratio was high, but in case of low EV ratio choice problems, they were more likely to use a heuristic strategy (PH). Additionally, more time spent on processing choice problems was associated with more CPT/EV choices. Last but not the least, we showed that the relationship between pupil size and choice was moderated by the EV ratio: choices consistent with PH predictions were less likely with higher pupil size but only in low EV ratio problems.

Our results replicated previous findings (Pachur *et al.*, 2013; Traczyk, Sobkow *et al.*, 2018). Participants made substantially more choices contingent upon the expectation models in high EV ratio problems in comparison to low EV ratio problems, suggesting that when a decision problem is computationally demanding (i.e., it is difficult to discriminate between gambles' EVs) or is relatively trivial (i.e., EVs of the two gambles are similar, which may result in equally good payoff), people tend to select a choice strategy contingent on the task structure and its requirements. This result is in line with the notion that people adaptively employ decision strategies according to the decision environment (Payne *et al.*, 1993). Firstly, choice strategies contingent upon expectation models has been shown to demand more cognitive resources than heuristics. Secondly, choice problems with a high EV ratio seem to be computationally less difficult, since difference between gambles is easily discernible. Indeed, we showed that in low EV ratio problems, people made decisions predicted by PH rather than CPT/EV. This might suggest that one might not need to engage cognitive effort in low EV ratio problems, because they are too trivial in terms of maximising payoffs. At the same time, more meaningful problems (those with high EV ratio and high payoff) were more likely to be predicted by CPT/EV.

Interestingly, findings based on choices were only partially supported by process-tracing measures. We did not find any evidence to corroborate that pupil size is larger in choices predicted by CPT/EV models than in those predicted by PH. Additionally, it appears that none of the employed variables was a credible predictor of pupil size. However, we found that longer time spent on processing choice problems was related to more choices being consistent with CPT/EV predictions. This is in line with previous results indicating that deliberation on a choice problem that is often operationalised by longer response time (Ghazal *et al.*, 2014; Petrova *et al.*, 2016, 2018) is associated with normatively better decisions. We believe that it is worth further investigating mutual relationships between deliberation and cognitive effort to assess their relative contribution in decision-making processes.

Notably, we found a credible interaction of choice problem and pupil size that predicted choices. In high EV ratio problems, the dominant proportion of choices predicted by CPT/EV strategy was relatively equally distributed across the whole range of values of pupillary response. However, although generally low EV ratio problems resulted in choices predicted by PH, we can notice decreasing number of PH choices (therefore increasing number of CPT/EV choices) with an increasing pupil size. This result indicates that EV ratio moderated the relationship between pupil size and choice, suggesting that choices predicted by expectation models required more processing information, but only when the difference between options is vague and maximising EV is challenging. Contrarily, in high EV ratio problems where it was reasonable to find better option due to easily discernible difference between EVs, people might have saved their cognitive resources and instead make choices that are predicted by seemingly more computationally demanding strategy (i.e., CPT/EV). Glöckner *et al.* (2012) found that in the decisions from description, pupil size increased with decreasing EV difference (a measure similar to EV ratio). In contrast, these results were not found in Fiedler and Glöckner (2012). Even though we did not find any evidence that pupil size is larger in choices with smaller differences between EVs, we observed an interesting interaction predicting choices. The likelihood of choices predicted by PH diminished in favour of CPT/EV, with increasing pupil size appearing in choice problems with high similarity between EVs. Still we need more evidence to clarify the relationship between pupil size and choice that is potentially moderated by EV ratio.

Future studies should extend the findings of the present research and overcome some its limitations. It seems interesting to use a different set of choice problems and other process-tracing measures. In the current study, CPT/EV choices could be also predicted by other heuristics such as maximax heuristic. Despite previous studies (Pachur *et al.*, 2013), using the same set of choice problems, documented that maximax heuristics did not predict choices better than chance, in the current study, we did not measure acquisition frequencies nor the direction of search, and therefore, we were not able to combine choices with cognitive processes. Future studies should solve this problem by employing gambles that are free of these limitations and including more rigorous process-tracing methods.

Also, we find it essential to address the role of cognitive abilities in this effect in a more diversified population. For instance, it has been repeatedly documented that people with high numeracy abilities (i.e., the ability to understand and use the concept of probability and statistical information; Cokely *et al.*, 2018; Cokely, Galesic, Schulz, Ghazal, Garcia-Retamero, 2012; Garcia-Retamero, Sobkow, Petrova, Garrido, Traczyk, 2019) are more sensitive to expected value variations (Jasper, Bhattacharya, Levin, Jones, Bossard, 2013; Peters, Bjalkebring, 2014), better estimate probabilities from frequencies (Traczyk, Sobkow, Matukiewicz, Petrova, Garcia-Retamero, 2020), make more adaptive choices (Jasper *et al*., 2013; Traczyk, Sobkow *et al*., 2018), and elaborate more (i.e., sample more information) on a choice problem (Ashby, 2017; Traczyk, Lenda *et al*., 2018). Taken these findings into account, people with high numeracy, in comparison to people with low numeracy, should make normatively better and adaptive decisions by deliberating more on choice problems, especially in loss domain. Nevertheless, predictions regarding cognitive effort are not so clear. On the one hand, more numerate people can be able to engage more cognitive resources while processing a choice problem. On the other hand, they can save their cognitive resources by engaging a minimal effort for a longer time spent on processing the problem.

Bibliography

Ashby, N. J. S. (2017). Numeracy Predicts Preference Consistency: Deliberative Search Heuristics Increase Choice Consistency for Choices from Description and Experience. *Judgement and Decision Making*, *12*(2), 128–139.

Barr, D. J. (2008). Memory and Language Analyzing ‘Visual World’ Eyetracking Data Using Multilevel Logistic Regression. *Journal of Memory and Language*, *59*(4), 457–474. https://doi.org/10.1016/j.jml.2007.09.002.

Bernoulli, D. (1954). Exposition of a New Theory on the Measurement of Risk. *Econometrica*, *22*(1), 23. https://doi.org/10.2307/1909829.

Bradley, M. M., Miccoli, L., Escrig, M. A., Lang, P. J. (2008). The Pupil as a Measure of Emotional Arousal and Autonomic Activation. *Psychophysiology*, *45*(4), 602–607. https://doi.org/10.1111/j.1469-8986.2008.00654.x.

Brandstätter, E., Gigerenzer, G., Hertwig, R. (2006). The Priority Heuristic: Making Choices without Trade-offs. *Psychological Review*, *113*(2), 409–432. https://doi.org/10.1037/0033-295X.113.2.409.

Cavanagh, J. F., Wiecki, T. V., Kochar, A., Frank, M. J. (2014). Eye Tracking and Pupillometry Are Indicators of Dissociable Latent Decision Processes. *Journal of Experimental Psychology. General*, *143*(4), 1476-1488. https://doi.org/10.1037/a0035813.

Cokely, E. T., Feltz, A., Ghazal, S., Allan, J. N., Petrova, D. G., Garcia-Retamero, R. (2018). Decision Making Skill: From Intelligence to Numeracy and Expertise. In K. A. Ericsson, R. R. Hoffman, A. Kozbelt, A. M. Williams (eds), *The Cambridge Handbook of Expertise and Expert Performance* (2nd ed., pp. 476–505). New York, NY: Cambridge University Press.

Cokely, E. T., Galesic, M., Schulz, E., Ghazal, S., Garcia-Retamero, R. (2012). Measuring Risk Literacy: The Berlin Numeracy Test. *Judgment and Decision Making*, *7*(1), 25–47.

Fiedler, S., Glöckner, A. (2012). The Dynamics of Decision Making in Risky Choice: An Eye-tracking Analysis. *Frontiers in Psychology*, *3*, 1–18. https://doi.org/10.3389/fpsyg.2012.00335.

Garcia-Retamero, R., Sobkow, A., Petrova, D., Garrido, D., Traczyk, J. (2019). Numeracy and Risk Literacy: What Have We Learned So Far? *The Spanish Journal of Psychology*, *22*(E10), 1–11. https://doi.org/10.1017/sjp.2019.16.

Gelman, A. (2008). Scaling Regression Inputs by Dividing by Two Standard Deviations. *Statistics in Medicine*, *27*(15), 2865–2873. https://doi.org/10.1002/sim.

Gelman, A., Lee, D., Guo, J. (2015). Stan: A Probabilistic Programming Language for Bayesian Inference and Optimization. *Journal of Educational and Behavioral Statistics*, *40*(5), 530–543.

Ghazal, S., Cokely, E. T., Garcia-Retamero, R. (2014). Predicting Biases in Very Highly Educated Samples: Numeracy and Metacognition. *Judgment and Decision Making*, *9*(1), 15–34.

Gigerenzer, G., Goldstein, D. G. (1996). Reasoning the Fast and Frugal Way: Models of Bounded Rationality. *Psy-*

chological Review, *103*(4), 650–669. Retrieved from http://psycnet.apa.org/journals/rev/103/4/650.html.

Gigerenzer, G., Todd, P. M., ABC Research Group. (1999). *Simple Heuristics that Make Us Smart*. New York: Oxford University Press.

Glöckner, A., Fiedler, S., Hochman, G., Ayal, S., Hilbig, B. E. (2012). Processing Differences between Descriptions and Experience: A Comparative Analysis Using Eye-tracking and Physiological Measures. *Frontiers in Psychology*, *3*(JUN), 1–15. https://doi.org/10.3389/fpsyg.2012.00173.

Hochman, G., Yechiam, E. (2011). Loss Aversion in the Eye and in the Heart: The Autonomic Nervous System's Response to Losses. *Journal of Behavioral Decision Making*, *24*, 140–156. https://doi.org/10.1002/bdm.692.

Jasper, J. D., Bhattacharya, C., Levin, I. P., Jones, L., Bossard, E. (2013). Numeracy as a Predictor of Adaptive Risky Decision Making. *Journal of Behavioral Decision Making*, *26*(2), 164–173. https://doi.org/10.1002/bdm.1748.

Kahneman, D., Beatty, J. (1966). Pupil Diameter and Load on Memory. *Science*, *154*(3756), 1583–1585. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/5924930.

Lakens, D. (2013). Calculating and Reporting Effect Sizes to Facilitate Cumulative Science: A Practical Primer for t-tests and ANOVAs. *Frontiers in Psychology*, *4*, 863. https://doi.org/10.3389/fpsyg.2013.00863.

Mathôt, S., Fabius, J., van Heusden, E., Van der Stigchel, S. (2018). Safe and Sensible Preprocessing and Baseline Correction of Pupil-size Data. Behavior Research Methods, *50*(1), 94–106.

Mathôt, S., Van der Stigchel, S. (2015). New Light on the Mind's Eye: The Pupillary Light Response as Active Vision. *Current Directions in Psychological Science*, *24*(5), 374–378. https://doi.org/10.1177/0963721415593725.

Pachur, T., Hertwig, R., Gigerenzer, G., Brandstätter, E. (2013). Testing Process Predictions of Models of Risky Choice: A Quantitative Model Comparison Approach. *Frontiers in Psychology*, *4*, 1–22. https://doi.org/10.3389/fpsyg.2013.00646.

Payne, J. W., Bettman, J. R. (2004). Walking with the Scarecrow: The Information Processing Approach to Decision Research. In N. Harvey, D. Koehler (eds), *The Blackwell Handbook of Judgment and Decision Making* (pp. 110–132). Oxford: Oxford University Press.

Payne, J. W., Bettman, J. R., Johnson, E. J. (1988). Adaptive Strategy Selection in Decision Making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 534. http://dx.doi.org/10.1037/0278-7393.14.3.534.

Payne, J. W., Bettman, J. R., Johnson, E. J. (1993). *The Adaptive Decision Maker*. Cambridge: Cambridge University Press.

Peters, E., Bjalkebring, P. (2014). Multiple Numeric Competencies: When a Number Is Not Just a Number. *Journal of Personality and Social Psychology*, (Advance online publication). https://doi.org/http://dx.doi.org/10.1037/pspp0000019.

Petrova, D., Garcia-Retamero, R., Catena, A., van der Pligt, J. (2016). To Screen or Not to Screen: What Factors Influence Complex Screening Decisions? *Journal of Experimental Psychology: Applied*, *22*(2), 247–260. https://doi.org/10.1037/xap0000086.

Petrova, D., Traczyk, J., Garcia-Retamero, R. (2019). What Shapes the Probability Weighting Function? Influence of Affect, Numeric Competencies, and Information Formats. *Journal of Behavioral Decision Making*, *32*(2), 124–139. https://doi.org/10.1002/bdm.2100.

Rubaltelli, E., Dickert, S., Slovic, P. (2012). Response Mode, Compatibility, and Dual-processes in the Evaluation of Simple Gambles: An Eye-tracking Investigation. *Judgment, Decision Making*, *7*(4), 427–440.

Salthouse, T. A., Ellis, C. L., Diener, D. C., Somberg, B. L. (1981). Stimulus Processing during Eye Fixations. *Journal of Experimental Psychology: Human Perception and Performance*, *7*(3), 611–623.

Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, *69*(1), 99. https://doi.org/10.2307/1884852.

Simon, H. A. (1990). Invariants of Human Behavior. *Annual Review of Psychology*, *41*(1), 1–20. https://doi.org/10.1146/annurev.ps.41.020190.000245.

Stan Development Team (2016). Rstanarm: Bayesian Applied Regression Modeling via Stan. R package version 2.13.1. http://mc-stan.org/.

Starmer, C. (2000). Developments in Non-expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk. *Journal of Economic Literature*, *38*(2), 332–382. Retrieved from http://www.jstor.org/stable/2565292.

Traczyk, J., Lenda, D., Serek, J., Fulawka, K., Tomczak, P., Strizyk, K., Polec, A., Zjawiony, P., Sobkow, A. (2018). Does Fear Increase Search Effort in More Numerate People? An Experimental Study Investigating Information Acquisition in a Decision from Experience Task. *Frontiers in Psychology*, *9*(1203). https://doi.org/10.3389/fpsyg.2018.01203.

Traczyk, J., Sobkow, A., Fulawka, K., Kus, J., Petrova, D., Garcia-Retamero, R. (2018). Numerate Decision Makers Don't Use More Effortful Strategies Unless It Pays: A Process Tracing Investigation of Skilled and Adaptive Strategy Selection in Risky Decision Making. *Judgment and Decision Making*, *13*(4), 372–381.

Traczyk, J., Sobkow, A., Matukiewicz, A., Petrova, D. G., Garcia-Retamero, R. (2020). The Experience-based Format of Probability Improves Probability Estimates: The Moderating Role of Individual Differences in Numeracy. *International Journal of Psychology*, 55(2), 273–281. https://doi.org/10.1002/ijop.12566.

Tversky, A., Kahneman, D. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323. https://doi.org/10.1007/BF00122574.

Wang, J. T. (2011). Pupil Dilation and Eye-tracking. In M. Schulte-Mecklenbeck, A. Kuhberger, R. Ranyard (eds), *Handbook of Process Tracing Methods for Decision Research. A Critical Review and User's Guide* (pp. 185–2014). New York: Psychology Press. Taylor, Francis Group.

Appendix

Proportions of CPT/EV Choices in Low EV Ratio Problems (with EV Ratios Around 1) and 12 High EV Ratio Problems (with EV Ratios between 5 and 6) Binary Choice Problems Consisting of Two-outcome Gambles in the Gain Domain. The Priority Heuristic (PH) and Cumulative Prospect Theory (CPT) Predicted the Opposite Choices. Each Problem Met Criteria of Non-dominance

Gamble A	Gamble B	EV Gamble A	EV Gamble B	EV Ratio	Choice by PH	Choice by CPT/EV	Proportion of CPT/EV Choices
5.40, 0.29; 0, 0.71	9.70, 0.17; 0, 0.83	1.57	1.65	1.05	A	B	0.33
17.50, 0.17; 0, 0.83	3.00, 0.94; 0, 0.06	2.98	2.82	1.05	B	A	0.24
9.70, 0.17; 0, 0.83	5.40, 0.29; 0, 0.71	1.65	1.57	1.05	B	A	0.29
3.00, 0.29; 0, 0.71	5.40, 0.17; 0, 0.83	0.87	0.92	1.06	A	B	0.29
31.50, 0.17; 0, 0.83	5.40, 0.94; 0, 0.06	5.36	5.08	1.05	B	A	0.24
31.50, 0.29; 0, 0.71	56.70, 0.17; 0, 0.83	9.14	9.64	1.06	A	B	0.29
9.70, 0.17; 0, 0.83	3.00, 0.52; 0, 0.48	1.65	1.56	1.06	B	A	0.14
5.40, 0.17; 0, 0.83	3.00, 0.29; 0, 0.71	0.92	0.87	1.06	B	A	0.33
3.00, 0.52; 0, 0.48	9.70, 0.17; 0, 0.83	1.56	1.65	1.06	A	B	0.24

Gamble A	Gamble B	EV Gamble A	EV Gamble B	EV Ratio	Choice by PH	Choice by CPT/EV	Proportion of CPT/EV Choices
17.50, 0.52; 0, 0.48	56.70, 0.17; 0, 0.83	9.10	9.64	1.06	A	B	0.1
9.70, 0.52; 0, 0.48	31.50, 0.17; 0, 0.83	5.04	5.36	1.06	A	B	0.19
56.70, 0.17; 0, 0.83	17.50, 0.52; 0, 0.48	9.64	9.10	1.06	B	A	0.19
3.00, 0.17; 0, 0.83	56.70, 0.05; 0, 0.95	0.51	2.84	5.56	A	B	0.48
3.00, 0.94; 0, 0.06	31.50, 0.52; 0, 0.48	2.82	16.38	5.81	A	B	0.67
56.70, 0.05; 0, 0.95	3.00, 0.17; 0, 0.83	2.84	0.51	5.56	B	A	0.57
5.40, 0.94; 0, 0.06	56.70, 0.52; 0, 0.48	5.08	29.48	5.81	A	B	0.71
31.50, 0.52; 0, 0.48	3.00, 0.94; 0, 0.06	16.38	2.82	5.81	B	A	0.57
56.70, 0.52; 0, 0.48	5.40, 0.94; 0, 0.06	29.48	5.08	5.81	B	A	0.62
3.00, 0.94; 0, 0.06	56.70, 0.29; 0, 0.71	2.82	16.44	5.83	A	B	0.48
5.40, 0.52; 0, 0.48	56.70, 0.29; 0, 0.71	2.81	16.44	5.86	A	B	0.67
31.50, 0.29; 0, 0.71	3.00, 0.52; 0, 0.48	9.14	1.56	5.86	B	A	0.62
56.70, 0.29; 0, 0.71	5.40, 0.52; 0, 0.48	16.44	2.81	5.86	B	A	0.57
3.00, 0.29; 0, 0.71	56.70, 0.09; 0, 0.91	0.87	5.10	5.87	A	B	0.48
56.70, 0.09; 0, 0.91	3.00, 0.29; 0, 0.71	5.10	0.87	5.87	B	A	0.57