Title

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Individual Differences in Gaze Dynamics in Risky Decision-making

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Abstract

In risky decision-making, expected utility (EU) theory is widely used to examine people's risk attitude and choice behavior. However, it is unknown how risk attitude relates to attention and information search. In this paper, we explore the relationship between risk attitude (as measured by a variant of EU) and eye movement patterns (which serve as a proxy for attention and information search). Participants made choices between gambles presented perceptually as flickering grids in which monetary values were indicated by colors and probabilities by color proportions. To explore attention and information search patterns, we investigated eye movement patterns when faced with different gambles and correlated these patterns with the parameters of EU. We observed that people who are more risk-seeking (as determined by modeling) tend to look at risky options more often. These results bridge choice behaviors conceptualized by EU and information search strategies under risky decision-making revealed by eye movements.

Keywords: risky decision-making; eye movements; cumulative prospect theory; hierarchical Bayesian parameter estimation; individual differences

Introduction

We face decision-making under risk every day in our lives, from financial investment decisions, choosing a new job, to voting for a presidential candidate. Lotteries, or gambles, consisting of well-defined sets of options, are widely used in psychological research to explore how people make decisions under risk. Expected Utility (EU) theory (Neumann & Morgenstern, 1947) has been widely used to predict choices with well-defined sets of gambles in different forms, but its connection to information search and attention (e.g., as measured by eye movements) has not been clearly revealed. For example, do people who are more risk-seeking look more often at risky options?

Eye movements, which have been studied as a process tracing methodology (Glaholt & Reingold, 2011), have been shown to be related to decisions under different tasks (Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011; Shimojo et al., 2003; Stewart, Hermens, & Matthews, 2016) and tested by different models (Brandstätter & Körner, 2014; Fiedler & Glökner, 2014). Nevertheless, the link between risk attitude revealed by EU and attention and information search strategy is still missing.

In the present study, participants were asked to make risky decisions between two gambles presented perceptually while their eye movements were monitored. Gambles were represented as a grid of colored pixels where the colors were associated with monetary amounts and the proportion of pixels with the probability of winning that amount. One gamble was risky (higher possible monetary payout, but lower probability) and one was safe (lower possible monetary payout, but higher probability). We used a variant of EU to model participants' choice behavior and then examined the relationship between model parameters and eye movement characteristics. This experimental paradigm enables us to bridge the gap between decision processes (as modeled by EU) and attention and information search patterns (as measured by eye movements).

Experiment: Speeded Risky Gambling

Participants

39 undergraduate students (31 female) from Vanderbilt University participated in the experiment for course credit. Their age ranged from 18 to 22 years old (mean = 19.3). We tested 28 participants with a right dominant eye and 11 with a left dominant eye.

Methods

All stimuli were presented on a 23.5-inch ViewSonic screen with a 60 Hz refresh rate at 1980 $\times$ 1020-pixel resolution. The viewing distance was 68 cm and each gamble had an overall size of 4.5° $\times$ 4.5° of visual angle. In this experiment, each trial began with a fixation cross displayed for 0.5 second. Following the fixation cross, two square grids were always presented diagonally at two of the corners on the screen for maximal 2 seconds. These two grids consisted of 20 $\times$ 20 10-pixel squares, which were filled in with grey indicating a zero payout and one of three colors (blue, rose, and yellow) indicating different positive monetary payouts that participants learned from instructions and practice. The proportion of color to grey (i.e., positive payout to zero payout) was randomly selected from 15 pairs of gambles (Table 1). Thus, participants were faced with a choice between two nonnegative gambles that offered different probabilities of winning different amounts of money. The configuration of colored elements in the grids was randomly rearranged every four frames to avoid potential perceptual pattern biases (thus the grids

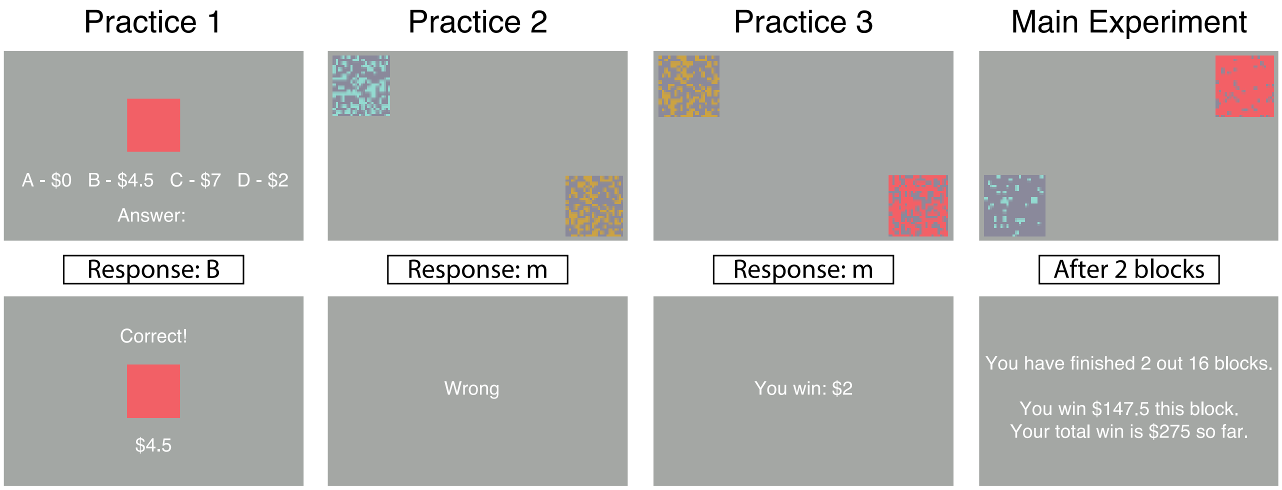

Figure 1. Speeded risky gambling experiment procedure. There were three practice blocks before the main task. In this case, rose, yellow, and blue represent $2, $4.5, and $7. In the second and the third practice blocks as well as the main task, participants pressed 'z' or 'm' to indicate choosing the left or the right grid, respectively. In practice block 2, participants were instructed to select the gamble with a higher expected value. The feedback indicated whether their choice was correct or not. In practice block 3, participants were allowed to select whichever gamble they preferred. They received feedback about their choices after every trial. In the main experiment, the participants received feedback at the end of blocks. There was no trial-by-trial feedback during the main task.

appeared to flicker). Participants were instructed to select the gamble that they wanted to play. The results of the chosen gambles were provided to participants during block breaks as their cumulative payouts.

Table 1: Gambles used in the Speeded Risky Gambling Task

v(R)	*p*(R)	*v*(S)	*p*(R)	ΔEV(R-S)
$4.5	0.46	$2	0.54	0.99
$7	0.33	$2	0.67	0.97
$7	0.48	$4.5	0.52	1.02
$4.5	0.38	$2	0.62	0.47
$7	0.28	$2	0.72	0.52
$7	0.43	$4.5	0.57	0.45
$4.5	0.31	$2	0.69	0.02
$7	0.22	$2	0.78	-0.02
$7	0.39	$4.5	0.61	-0.02
$4.5	0.23	$2	0.76	-0.49
$7	0.17	$2	0.83	-0.47
$7	0.35	$4.5	0.65	-0.48
$4.5	0.15	$2	0.85	-1.03
$7	0.11	$2	0.89	-1.01
$7	0.3	$4.5	0.70	-1.05

R denotes the risky gamble, S denotes the safe gamble

The experiment had three practice blocks before the main experiment, which consisted of 16 blocks (Figure 1). The first practice had 20 trials. In the first practice block, we asked participants to select the monetary value associated with a particular color and provided feedback based on their responses. In the second practice block, two grids were presented that had two different colors (i.e., different monetary amounts), but in the same proportions. Participants needed to choose the grid with the greater expected value (i.e., the grid with the color associated with the higher value). The third practice block was similar to the main experiment, except that feedback on the gambling results was provided for each trial. Both the second and the third practice had 15 trials. In the main experiment, each block had 66 trials of which 10% are catch trials. During block breaks, the payout for the current block and cumulative payout were provided. Each gamble pair had one risky gamble and one safe gamble. Risky gambles were defined as gambles where positive payouts were greater than that of safe gambles, but where probabilities of winning were less than that of safe gambles. The difference in expected values (ΔEV, defined as EV(risky gamble) – EV(safe gamble)) of 15 gamble pairs ranged from about -1 to 1 (Table 1). We had three gamble pairs for each ΔEV condition: $4.5 and $2, $7 and $2, and $7 and $4.5. Catch trials were gamble pairs where the risky gamble had a higher probability and greater monetary payout than the safe gamble.

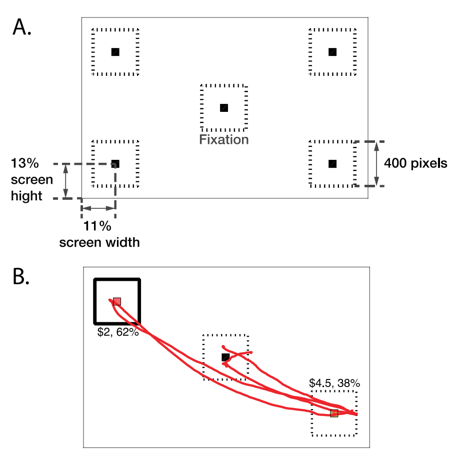

Figure 2. Panel A: Areas of interest diagram. Panel B: Representative eye trajectory (red lines) within one trial. Two gambles were presented diagonally in randomized locations. Solid black square is the center of fixation. Solid rose and yellow squares are the center of two gambles. Black squares are AOIs (solid: the chosen gamble; dotted: fixation area and the unchosen gamble).

Eye movements were monitored by an EyeLink 1000 desk-mounted eye tracker (SR Research, Ontario, Canada). We tracked participants' dominant eye movement with both pupil and corneal reflection settings at a sampling rate of 1000 Hz. Area of interest (AOI) was defined around the centers of the grids and fixation cross with the size of 400 × 400 pixels. We used these AOIs to determine when participants were looking at each gamble and to explore the gaze dynamics during their deliberation (Figure 2).

After the speeded risky gambling task, every participant completed a set of surveys, which included the Cognitive Reflection Test (CRT, Frederick, 2005), DOSPERT scale (Blais & Weber, 2006), and Holt and Laury gambles (Holt & Laury, 2002). In this paper, we did not include the results from the CRT, DOSPERT scale, and Holt and Laury gambles. Those results will be reported elsewhere.

Results

Two participants, one of whom had less than 30% correct on the catch trials, one who did not move his or her eyes at all throughout the experiment, and another five participants' data were not successfully recorded due to technical issues, were excluded. We first analyzed the effect of ΔEV and different gamble pairs on risky choices and response time. We observed that the probability of risky choice increased as the ΔEV increased (Figure 3A). The probabilities of risky choice under the three gamble pairs were different, with the probability of risky choice under the $7-$4.5 pair being the highest and the $7-$2 pair being the lowest. When ΔEV is greater than zero, which indicates that the risky gamble had a greater EV compared to the safe gamble, the risky gamble was more likely to be chosen. We used Bayesian methods to analyze the data and report the resulting Bayes Factors (BF), Based on a Bayesian two-way ANOVA, we found that the model with ΔEV and gamble pair without their interaction was preferred to all other models (BF_{Model} = 636.06) as well as to the null model ($BF_{10} = 2.03\times10^{37}$). The Bayes Factors for including the variables ΔEV, gamble pairings, and their interaction were $BF_{Inclusion} \sim \infty$, and $BF_{Inclusion}$ = 731.74, respectively. Regarding response time, risky decisions in general took longer as the ΔEV increased. Response time increased as ΔEV increased under the $7-$2 and $4.5-$2 pairs, but did not change much under the $7-$4.5 pair. Based on a Bayesian two-way ANOVA, we found that a model with both ΔEV and gamble pairings and no interaction was preferred to all other models (BF_{Model} = 580.70) as well as the null model ($BF_{10} = 2.36\times10^{13}$). The Bayes Factors for including ΔEV and gamble pair were $BF_{Inclusion} = 2.17\times10^2$ and $BF_{Inclusion} = 2.98\times10^2$, respectively.

Next, we used number of fixations to investigate information search patterns under the five ΔEV conditions with the three gamble pairs (Figure4A). The number of fixations is the average fixation count in non-catch trials prior to the decision. We observed that the number of fixations increased with increasing ΔEV, which was consistent with response time patterns. Based on a Bayesian two-way ANOVA, we found that the model with both ΔEV and gamble pair and no interaction was preferred to all other models (BF_{Model} = 133.90) as well as the null model ($BF_{10} = 5.32\times10^5$). The Bayes Factors for including ΔEV and gamble pair were $BF_{Inclusion} = 1.48\times10^3$ and $BF_{Inclusion}$ = 286.17, respectively.

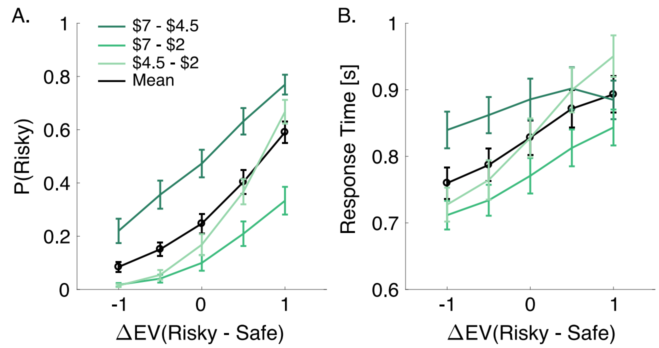

Figure 3. Psychometrics in speeded risky gambling experiment. Panel A: probability of risky choices under different ΔEV conditions. Panel B: the effect of different ΔEVs and gamble pairs on response time. Error bars are the standard error of the mean. Dark, medium, and light green lines represent the three gamble pairings.

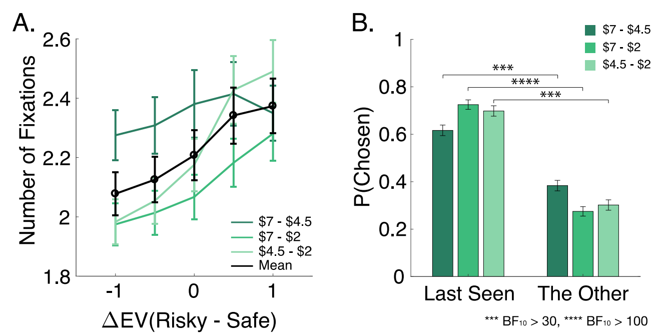

Figure 4. Eye movement results. Panel A: Fixation numbers under different ΔEV conditions. Panel B: Probability of choosing the last seen gamble and the other gamble. The error bars are the standard error of the mean.

We also observed the same gaze biases reported in previous studies showing that eye movements made during a choice have a strong relationship with the final choice (Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011; Stewart, Hermens, & Matthews, 2016). We compared choice proportions when the last gaze was on the chosen gamble with that of the unchosen gamble, and found that the last seen gamble was more likely to be chosen as compared to the other gamble for the three gamble pairs separately ($7-$4.5: BF_{10} = 37.93; $7-$2: $BF_{10} = 4.58\times10^4$; $4.5-$2: BF_{10} = 79.17) (Figure 4B). To investigate the influence of different gamble pairs on the relationship of last gaze and risky choices, we further examined the difference in proportion of risky choice given the first or the last gaze was in the AOI of the risky gambles. The first gaze had less influence on final choice of the risky gambles compared to the last gaze. For the three gamble pairs, the proportion of choices for the risky gambles was greater when the last gaze was on the risky gamble than when the last gaze was on the safe gamble (Table 2 and Figure 5).

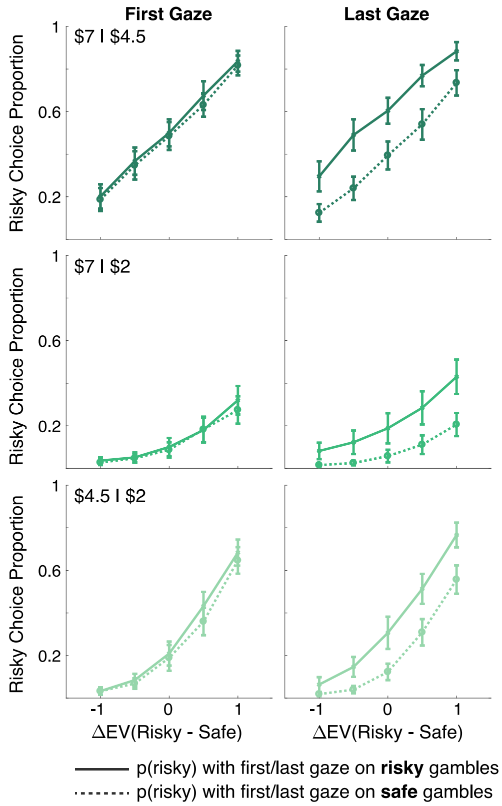

Figure 5. Proportion of risky choices given the first or last gaze was on the risky versus safe option. Solid lines: proportion of risky choices when the first or last gaze was on the risky gamble. Dotted lines: proportion of risky choices with the first or last gaze was on the safe gamble. The error bars are the standard error of the mean.

Table 2. Bayesian ANOVA for first and last gaze effects.

	Gamble pairs	Best model	BF_{model}	BF_{10}
First Gaze (FG) effect	\$7 - \$4.5	ΔEV	6.3	1.4×10^{24}
	\$7 - \$2	ΔEV	26.9	1.4×10^{17}
	\$4.5 - \$2	ΔEV	21.2	1.9×10^{55}
Last Gaze (LG) effect	\$7 - \$4.5	LG + ΔEV	146.9	2.8×10^{24}
	\$7 - \$2	LG + ΔEV	34.9	1.3×10^{17}
	\$4.5 - \$2	LG + ΔEV + LG*ΔEV	4.4	6.0×10^{53}

The first (last) gaze effect is the difference in the probability of selecting the risky option when the first (last) gaze is on the risky option as compared to the safe option.

Hierarchical Bayesian Parameter Estimation of "Perceptual" Expected Utility Theory

To account for choice behavior, we developed a "perceptual" variant of EU theory. The parameters of this model were estimated using a hierarchical Bayesian parameter estimation approach. There are two components of our variant of EU: (1) the subjective utility function and (2) the perception of probabilities. The subjective utility function is governed by alpha, which indicates an individual's risk attitude. If alpha is less than 1, it indicates that the person is risk-aversive. If alpha is greater than 1, it indicates that the person is risk-seeking. If alpha is equal to 1, that person is risk-neutral.

In EU theory, the subjective value of a two-outcome gamble G is determined by

$$EU(G) = p_1 u(x_1) + p_2 u(x_2), \tag{1}$$

where $u(\cdot)$ is the utility of the outcomes defined as

$$u(x_i) = x_i^{\alpha}, \tag{2}$$

where α is a free parameter that is greater than 0 and quantifies the curvature of the utility function.

In EU theory, the objective probabilities are used to compute the expected utilities of the gambles. In our experiment, however, the probabilities of both safe and risky gambles are presented as proportions of colors in the flickering grids. It is possible that people's perception or estimation of the actual proportion does not match the exact probabilities shown in the grids. That is, there may be perceptual distortion of the probability estimation. In order to capture this feature, we assume that perceived probability is given by the following function:

$$p_{perceived} = \frac{p_{objective}{}^{\beta}}{\varphi^{\beta} + p_{objective}{}^{\beta}} \tag{3}$$

where φ is the adaptation level for the proportion of color in the grid and β is a shape parameter. The probability of choosing option A over option B is modeled as:

$$p(A, B) = \frac{EU(A)}{EU(A)+EU(B)} \tag{4}$$

Hierarchical modeling serves as a compromise between a no-individual-differences model and a full-individual-differences model. In a hierarchical model, individual parameters are drawn from group-level distributions, usually normal distributions with estimated mean and standard deviation. The estimated means quantify different cognitive processes. The standard deviations quantify the similarity among individual participants' behavior.

We used the prior distributions for these three parameters as following. Individual α_i is drawn from the normal distribution with two group-level parameters $\mu^{\alpha} \sim U(0,5)$ and $\sigma^{\alpha} \sim U(0,10)$. Individual φ_i is drawn from the normal distribution with two group-level parameters $\mu^{\varphi} \sim U(0,100)$ and $\sigma^{\varphi} \sim U(0,10)$. Individual β_i is from the normal distribution with its group-level parameter $\mu^{\beta} \sim U(0,100)$ and $\sigma^{\beta} \sim U(0,10)$. We implemented the hierarchical EU model in JAGS. Posterior distributions were approximated by 3 MCMC chains with 5000 samples from each chain, after a burn-in of 1000 samples. Convergence of chains was evaluated by computing the $\hat{R}$ statistic. Figure 6 shows the posterior distributions of three group-level means. The means of μ^{α}, μ^{φ}, and μ^{β} are 0.92, 0.41, and 13.13, respectively.

By comparing observed choices with the predicted choices, we are able to assess how accurately the model captures people's choice behavior. We plot the observed risky choice proportions from the data with the posterior predictive of the model using the individual-level parameters (Figure 7). The model predictions are reasonably close to the actual proportion of risky choices indicating that the model accounts for the group-level data.

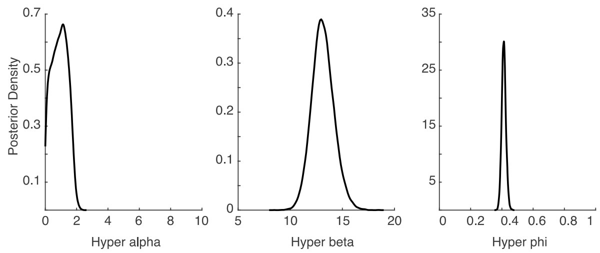

Figure 6. Posterior distributions of EU group-level parameters.

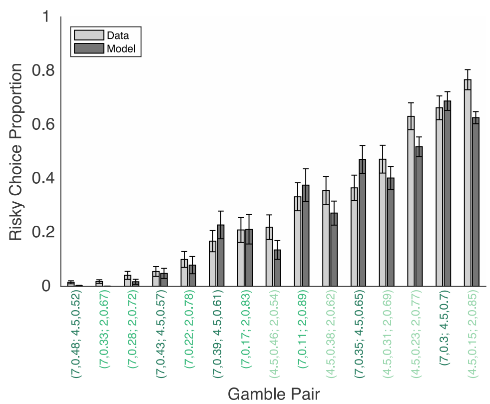

Figure 7. Comparison of the risky choice proportions from the data and predicted by EU theory. Light grey bins represent risky choice proportion from data, and dark grey bins represent risky choice proportion predicted by EU theory.

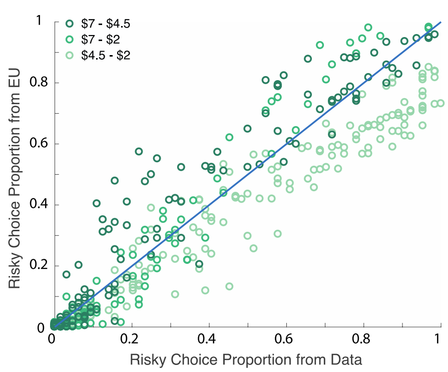

Figure 8. Comparison of risky choice proportion from the data and that predicted by EU. The line is y = x.

To examine the performance of EU theory at the individual level, we plot the individual data and predictions from EU theory using the individual-level parameters (Figure 8). Most of the data points fall on the diagonal, meaning that the performance of EU is reasonable at the individual level as well.

Individual differences in gaze dynamics

To bridge the gap between the conceptualized EU model and actual information search dynamics, we examined the correlation of EU parameters and eye movement statistics. We examined the correlations with four eye movement measures: % of trials with first fixation on risky, % of trials with last fixation on risky, proportion of gaze duration on risk, proportion of gaze duration on chosen gambles, as well as response time. See Table 3 for definitions of these five measures.

In EU, the parameter α captures participants' risk preferences. Note that EU assumes that the subjective utility function is concave if 0 < α < 1, implying that people are risk-averse, while the subjective utility function is convex if α > 1, implying that people are risk-seeking. A larger value of α implies less risk-aversion (or relatively greater risk-seeking behavior). We found that α was positively correlated with % of trials with last fixation on risky and proportion of gaze duration on risky gamble (see Table 3). For the two measures, the BF_{10} was greater than 100, indicting extremely strong support for the correlations. These correlations suggest that people who are more risk-seeking tend to look more at risky options.

Table 3. Correlations and Bayes Factors (BF) between eye movement statistics, response time, and EU parameters

Eye movement measures	EU parameters α	φ	β
% of trials with first fixation on risky	0.31 (0.942)	-0.47 (7.21)	-0.14 (0.29)
% of trials with last fixation on risky	0.65*** (479.29)	-0.60*** (133.72)	-0.14 (0.30)
proportion of gaze duration on risky	0.70*** (2787.37)	-0.73*** (11149.51)	-0.23 (0.46)
proportion of gaze duration on chosen	-0.14 (0.29)	-0.17 (0.33)	0.05 (0.23)
response time	0.38 (1.87)	-0.29 (0.76)	0.004 (0.22)

BF_{10} enclosed in parentheses. * $BF_{10} > 10$, ** $BF_{10} > 30$, *** $BF_{10} > 100$

- *% of trials with first fixation on risky*: proportion of trials in which the first fixation after gambling presentation was on the risky.
- *% of trials with last fixation on risky*: proportion of trials in which the last fixation before decisions were made was on the risky.
- *proportion of gaze duration on risk*: ratio of gaze duration on the risky to the response time of each trial.
- *proportion of gaze duration on chosen*: ratio of gaze duration on the chosen gamble to the response time of each trial.
- *response time*: from stimuli onset to responses by pressing keys.

The parameter φ determines the adaptation level of the perceived probability transform function. When $\varphi < 0.5$, individuals are more adapted to small probabilities, which also correspond to riskier options in our task (i.e., risky gambles in our experiment have high values and small probabilities). Thus, smaller values of φ indicate increased adaptation for risky options. We found that the parameter φ was negatively correlated with % of trials with the last fixation on risky and the proportion of gaze duration on risky.

The β parameter is the shape parameter for the probability transform function. This parameter was not correlated with any of the eye movement measures we calculated.

Discussion

In this study, we investigated the relationship between gaze dynamics and "perceptual" EU parameters in risky decision-making. First, we corroborated previous findings that the last fixation was closely related to actual choices (Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011; Shimojo et al., 2003; Stewart, Hermens, & Matthews, 2016). Going beyond this, we observed that people with different risk attitudes have different patterns of eye movements, which serve as a proxy for information search and attention. In particular, we found that (i) the utility shape parameter of EU was positively correlated with measures related to gaze duration on the risky option and to the proportion of last gaze on the risky option, and (ii) the adaptation level in perceived probability was negatively correlated with the proportion of the last gaze on the risky option and with the gaze duration on the risky option. These results establish the connection between risky choice behavior conceptualized by EU and information search strategies under risky decision-making revealed by gaze dynamics.

Given the fact that eye movements are only considered as a proxy of internal processes of attention, we cannot rule out the possibility that participants held the two gambles in a mental comparison while moving their eyes. Thus, we cannot conclude that the decision processes conceptualized by the EU model caused specific information search strategies or vice versa. Future studies are needed to explore the causal relationship between gaze dynamics and choice. For example, future studies could examine if changing information search strategies by manipulating the salience of risky gambles might influence people's risky choices. Also, manipulating exposure time of options might influence choices.

We conclude by addressing some of the limitations of the present study. First, all thirty-nine students were granted course credit regardless of their performance. It is possible that their behavior might change if there was actual monetary reward rather than a hypothetical situation. The three estimated parameters of EU might be different when participants are more engaged to maximize their final payouts (Holt & Laury, 2002). Second, in this study we did not include gambles with pure losses or mixtures of both gains and losses. People may adopt different strategies in this speeded risky gambling task when losses are introduced. Addressing these issues would be suitable for future studies. Nevertheless, we did observe individual differences in risk preferences as measured by EU and these differences where related to differences in gaze dynamics. This suggests that information search and attention is related to underlying decision processes.

Acknowledgement

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