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MAKING CHOICES IN REPETITIVE RISKY SITUATIONS WITH IMMEDIATE FEEDBACK

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ABSTRACT. This study examines decision-making behavior under risk using a repeated choices experimental design with immediate feedback. The aim is to investigate the heuristics of choice under risk and their performance when feedback is provided immediately after each decision. The experimental results reveal that participants demonstrate a notable inclination to take risks, which is consistent with prior research indicating an increase in risk-taking with experience. Furthermore, the overall performance of the 11 tested heuristics in predicting participant decisions is found to be relatively low, with the 'least likely' heuristic emerging as the top performer and the 'minimax' heuristic exhibiting poor performance across all measures and decision problem types.

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Introduction

In repeated risky situations where immediate feedback is obtained, learning about heuristics – i.e., rules used to simplify complex problems and aid in making faster choices (Gigerenzer, Todd, & the ABC Research Group, 1999) – can provide valuable insights into decision-making processes. However, it is worth noting that most experimental studies tend to avoid providing immediate feedback. While numerous studies examine repeated choices under risk, the majority of such research provides feedback on the effects of choices only after the entire data collection is completed, to inform about the resulting rewards (the review of such research can be found in Booij, Van Praag, & Van De Kuilen, 2010; and Fox & Poldrack, 2014). Consequently, most of our knowledge about how people choose between risky alternatives concerns choices with postponed feedback. However, the immediacy of feedback condition might be important when it comes to the way individuals experience risk and adopt risk attitudes (Li et al., 2023; Forlicz & Rólczyński, 2022; Petrakova et al., 2023).

There are two main approaches to describing decision-making under risk. The first approach applies models of choice, with the von Neumann and Morgenstern (1953) expected utility model and the Kahneman and Tversky (1979) prospect theory as the two representations that are most valuable from a descriptive point of view. The second approach is based on heuristics. Glöckner and Pachur (2012) describe these two approaches as models with adjustable parameters (choice theories) and models without adjustable parameters (heuristics). The first approach allows for fitting the data using subjective parameters adjustable to individual subjects, while the second approach remains invariant to the subject making the decision.

Nonetheless, these two approaches should not be treated as competing ones; there is great value in treating them as complementary. For instance, Tversky and Kahneman (1992), in addition to formulating cumulative prospect theory, which they consider approximate and incomplete, claimed that when people face complex problems, they employ a variety of heuristic procedures. However, they also noted that analyzing choice heuristics can be challenging due to their dependency on problem formulation and the contextual factors influencing choice. When evaluating the advantages and disadvantages of these two approaches, Glöckner and Pachur (2012) highlighted transparency and control over unsystematic variability as advantages of heuristic approach. Conversely, they identified relatively narrow applicability and limited scope, as well as inferior predictive power compared to parametric models, as the main drawbacks of the heuristic approach.

After over fifty years of systematic research on binary choice over risk, we have gained a significant amount of knowledge about decision-making tendencies and common errors (Kahneman & Tversky, 2000). There is ample evidence that people exhibit risk aversion when making choices involving gains, and risk-seeking behavior when faced with choices involving losses (Kahneman & Tversky, 1979; Starmer, 2000; Tobler & Weber, 2014; Valls Martínez et al., 2022). Moreover, individuals have been found to be loss averse, meaning they tend to assign greater weight to potential losses compared to equivalent gains (Ert & Erev, 2013; Schmidt & Traub, 2002; Tversky & Kahneman, 1992). This aversion to losses often leads to risk avoidance in various real-life situations (Camerer, 2000), even if it results in a disadvantageous choices. Additionally, the effect of such risk and loss aversion may manifest as information avoidance (Blajer-Gołębiewska, Wach, & Kos, 2018; Ho, Hagmann, & Loewenstein, 2020), preventing individuals from learning about the consequences of risky choices.

In order to incentivize individuals to make choices that are most profitable for them, for instance through behavioral interventions, it is important to further understand the effects on individuals' decision-making and their ability to adapt to risky situations of such factors as immediate feedback and the repeated risk-taking. We believe that through investigating how the heuristics of choice under risk apply to the repeated decisions with immediate feedback, we can learn more about patterns of such choices. Therefore, this study aims to investigate the heuristics of choice under risk and its performance when feedback is provided immediately after each decision.

The remainder of the paper is structured as follows. First, we develop hypotheses based on the literature review regarding the heuristics and risky choices with immediate feedback condition. An in-depth description of the research design together with an explanation of the examined heuristics is given in the section 2, whereas in the section 3 we provide crucial information on the experimental design and data collection. The obtained results are discussed also in the section 3.

1. Literature review

In real-world environments individuals often face repeated situations where risks are involved and immediate feedback is available (Gigerenzer et al., 1999; Kuděj et al., 2023; Civelek, et al., 2023; Turek et al., 2023). In such situations often heuristics enable individuals to make efficient choices based on experience and pattern recognition, particularly in time-sensitive and high-pressure situations, like within the sports and healthcare domains.

For instance, in basketball, players often use a recognition heuristic to quickly assess the best course of action in a dynamic and fast-paced game. Experienced players develop an intuitive sense of the game through years of practice and exposure. They rely on pattern recognition and heuristics to make split-second decisions, such as passing, shooting, or dribbling, without consciously analyzing every option. This heuristic enables players to react rapidly to changing situations on the court (Macquet, 2009).

Medical professionals frequently employ heuristics to aid in diagnosis and treatment decisions. For instance, in emergency medicine, the ABCDE heuristic (Airway, Breathing, Circulation, Disability, Exposure) helps prioritize patient care. When faced with a critical situation, doctors and nurses quickly assess and address these vital components first, ensuring the patient's immediate needs are met. This heuristic acts as a cognitive shortcut to initiate life-saving interventions promptly, even before conducting a comprehensive examination (Ferrari, 2020; Thim, Krarup, Grove, Rohde, & Lofgren, 2012).

Especially in situations where time and knowledge are limited, fast and frugal heuristics are applied due to their high adaptability. The fast and frugal heuristics were investigated by Gigerenzer, Todd, & the ABC Research Group (1999), who discuss two types of heuristics: process-oriented and outcome-oriented. The process-oriented approach focuses on the order of information acquisition, while the outcome-oriented approach focuses on the decision process's outcomes. Brandstätter, Gigerenzer and Hertwig (2006) classify heuristics into two groups: lexicographic rules and tallying. The lexicographic rules are based on ordering reasons according to a specific criterion. The reasons are considered, and the decision is ultimately based on one of them. The tallying group assumes that equal weights are assigned to different reasons, and the choice is made based on the reason that is supported by the most reasons.

The risky choice heuristics are the rules that indicate the choice for two-alternative choice problems. Such heuristics can be grouped into two categories: outcome-oriented and dual, with the latter referring to the combination of features, including outcomes and probabilities. The outcome-oriented risky choice heuristics include: equiprobable, equal-weight, minimax, maximax, and better than average. Among the dual heuristics, there are: priority, tallying, most likely, lexicographic, least-likely, and probable (Brandstätter et al., 2006). These heuristics are further characterized in section 2.

Brandstätter, Gigerenzer and Hertwig (2006) tested the performance of the risky choice heuristics against the parametric models. They measured the performance by calculating the proportion of decision problems in which the heuristic correctly predicted the majority of responses. They investigated four different sets of decision task from four research: (1) Kahneman and Tversky (1979), (2) Lopes and Oden (1999), (3) Tversky and Kahneman (1992), and (4) Erev et al. (2002), along with the reported majority choices from these studies. This study found that the priority heuristic outperformed all other models significantly in sets (1)-(3) with correct prediction for 100%, 87% and 89% of problems, and also provided predictions at a similar level to parametric models in set (4). The second-best performing heuristic was the equiprobable heuristic, which achieved an accuracy of 71% and 79% in sets (1) and (3), respectively. However, this heuristic performed poorly in set (4) with an accuracy level of only 20%. Interestingly, the study revealed that in sets (1) and (3), outcome-oriented heuristics performed better than those incorporating probability information. Conversely, in set (4), outcome heuristics performed worse than those considering probability information. No such distinction was observed in set (2). These results indicate that the decision strategy depends on the type of decision problem.

Glöckner and Pachur (2012) also tested the performance of the same 11 heuristics against the parametric models, especially Cumulative Prospect Theory. They measured the performance of the models (heuristics including) with the average in predicting participants' individual choices. They found the parametric models, which capture the individual variability of subjects, outperforming the heuristics, yet regarding the heuristics they concluded that the best performing ones were the priority heuristic and the minimax heuristic. Those two heuristics were able to explain slightly over 61% of the choices, while the worst performing heuristic maximax explained 49.2% of choices.

We believe that the experimental design, which includes repeated choices allowing for gaining experience, and immediate feedback facilitating learning, will have an impact on the results. Tobler and Weber (2014) observed that the volatility in responses is higher in decisions from experience compared to decisions from description. Recent experience and adaptive learning, which increase familiarity with risky choice options, can lead to a decreased perception of riskiness associated with those options.

Hertwig et al. (2004) found a significant difference between decisions made from experience and decisions made from description. In the feedback and experience condition, where subjects gradually acquired knowledge about the payoff distributions, the rate of risky choices was significantly higher compared to the description treatment, which provided a description of the two options. Similarly, Barron and Erev (2003) found an increase in risky choices for both gains and losses in decisions made from experience when decision-makers learned from feedback during the experiment. Conversely, Li et al. (2023) found immediate feedback to reduced risk-taking, and Abdellaoui, L'Haridon, and Paraschiv (2011) found no difference between the description and experience conditions.

Multiple studies have provided evidence supporting the notion that immediate feedback enhances learning and the acquisition of experience (Kulik & Kulik, 1988). As a result of learning, individuals who have gained experience tend to make choices that align more closely with the expected value, thereby reducing risk aversion behavior. Ert and Haruvy (2017) demonstrated that repeated exposure to the Holt-Laury test resulted in a shift from risk aversion to risk neutrality among subjects. Melesse and Cecchi (2017) examined the risky choices of farm households and discovered that market experience mitigates risk aversion tendencies. Bradbury, Hens, and Zeisberger (2015) found that simulated experience enhanced participants' understanding of risk and encouraged them to select riskier financial products, leading to increased risk-taking behavior. Similarly, Kaufmann, Weber, and Haisley (2013) demonstrated that experience sampling, as a method of communicating risk to investors, heightened their inclination to allocate more funds to risky investments.

Basing on those findings we expect to find more risk-seeking choices in the immediate feedback experiment in comparison to results reported in literature, from experiments with postponed feedback. Hence, we formulate Hypothesis 1.

H1: The proportion of risky choices is positively associated with experience.

Usually, experiments on risky choices focus on investigating risk attitudes or modeling preferences using choice models and estimating subjective parameters of such models (Abdellaoui, Bleichrodt, L'Haridon, & Paraschiv, 2013; Abdellaoui, Diecidue, & Öncüler, 2011; Booij et al., 2010; Tanaka, Camerer, & Nguyen, 2010). Risk attitudes, such as risk aversion, risk seeking, and risk neutrality, are typically observed through choices between risky and safe (certain) alternatives. Risk aversion is recognized when the subject rejects the risky gamble in favor of a certain amount equal to the expected value of the gamble. Conversely, a risk-seeking attitude entails preferring the gamble over certainty, while risk neutrality indicates indifference between the gamble and a certain payoff of the same expected value (Wakker, 2010, p. 52).

According to the prospect theory, majority of individuals choosing between gain lotteries reveal risk aversion, while they are risk-seeking when losses are involved (Kahneman & Tversky, 1979). Therefore, even in the immediate feedback condition, we expect the proportion of risky choices to be higher for loss lotteries compared to gain lotteries. However, we do not have specific expectations regarding the share of risky choices in decision problems involving mixed lotteries. Hence, we formulate Hypothesis 2.

H2: There is a relationship between the proportions of risky choices and the task type.

We have not found any evidence regarding the differential performance of heuristics in different outcome domains, specifically gains and losses. However, considering that individuals exhibit different risk attitudes in these two domains and taking into account the mixed results reported by previous studies regarding heuristics' performance in various choice outcome domains, it is reasonable to expect that individuals may alter their choice strategies depending on the outcome domains. Based on this observation, we propose Hypothesis 3.

H3: There is a relationship between the task type and the accuracy of the heuristics' prognoses.

2. Methodological approach

2.1. Research design

Our research concept is organized around three steps presented on Figure 1. First, we design an individual choice under risk experiment within the predefined conditions. The assumed conditions are the immediate feedback, financial consequences of decisions and postponed financial reward. Each subject is solving the sequence of decision problems, that require choosing the preferred lottery from the pair of lotteries. After each decision, the subject is exposed to the immediate feedback, which is an outcome that comes from the realization of the chosen lottery's probability distribution. Also, to provide the financial consequences of the decisions, we introduce the incentives' system, which encompasses all types of lotteries: gain, loss and mixed ones. Finally, the payment of the financial reward won in each session is postponed till after completing all experimental sessions.

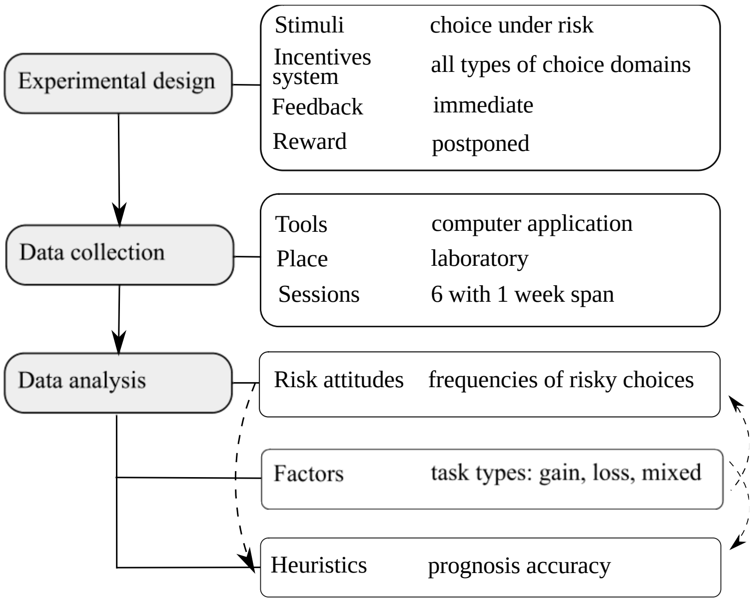

Figure 1. Research design diagram
Source: *own elaboration*

The second step is the data collection. Data comes from computerized experiment handled by a tool which is tailor-made application created for our research purpose. To obtain the individual data in the controlled setting we conduct the laboratory experiment organized in sessions with a weeks' span. As each experimental task (decision problem) requires cognitive effort from participants thus splitting up experiment into sessions lowers cognitive effort needed from participants in each session. Consequently, we conduct six sessions which ensures appropriate attention endurance of the participants.

Data analysis encompasses two areas of interest: risk attitudes and heuristics. The former is measured by the share of the participants' risky choices, whereas the latter is the accuracy of the heuristics' prognoses. Next, we verify the significance of the task type factor for risk attitude and heuristics' prognosis accuracy. The task type covers three output contexts: gains, losses and mixed lotteries.

2.2. Description of examined heuristics

Heuristics provide a description of the successive stages of a decision process (Gigerenzer et al., 1999, p. 142). In the current study, we investigate binary risky choices, which refer to choices made between pairs of gambles (lotteries, alternatives). Each gamble is characterized by explicitly provided outcomes (gains or losses) and the associated probabilities.

The decision strategies for risky choices are presented after Glöckner and Pachur (2012, p. 26) and Brandstätter et al. (2006). 11 heuristics were tested, and the decision process description for each heuristic is as follows.

- **Priority heuristic**: Examine the reasons in the following order: minimum gain, probability of minimum gain, and maximum gain. Stop the examination if the difference between the minimum gain and the maximum gain is equal to or greater than 1/10 of the maximum gain. Otherwise, stop the examination if the difference between the probabilities is equal to or greater than 1/10 of the probability scale. Choose the gamble with the more appealing gain (or probability). For loss gambles, the heuristic remains the same, except that 'gains' are replaced with 'losses'. For mixed gambles, the heuristic remains the same, except that 'gains' are replaced with 'outcomes'.

- **Equiprobabl**e: Calculate the arithmetic mean of all outcomes for each gamble. Choose the gamble with the highest mean.
- **Equal weight**: Calculate the sum of all outcomes for each gamble. Choose the gamble with the highest sum.
- **Better than average**: Calculate the grand average of all outcomes from all gambles. For each gamble, count the number of outcomes equal to or above the grand average. Then choose the gamble with the highest number of such outcomes.
- **Tallying**: Give a tally mark to the gamble with (a) the higher minimum gain, (b) the higher maximum gain, (c) the lower probability of the minimum gain, and (d) the higher probability of the maximum gain. For losses, replace 'gain' with 'loss' and 'higher' with 'lower' (and vice versa). Choose the gamble with the highest number of tally marks.
- **Probable**: Categorize probabilities as either probable (i.e., $p \geq 0.50$ for a two-outcome gamble, $p \geq 0.33$ for a three-outcome gamble, etc.) or improbable. Cancel out improbable outcomes. Then calculate the arithmetic mean of the probable outcomes for each gamble. Finally, choose the gamble with the highest mean.
- **Minimax**: Choose the gamble with highest minimum outcome.
- **Maximax**: Choose the gamble with the highest outcome.
- **Lexicographic**: Determine the most likely outcome of each gamble and choose the gamble with the better outcome. If both outcomes are equal, determine the second most likely outcome of each gamble, and choose the gamble with the better (second most likely) outcome. Proceed until a decision is reached.
- **Least likely**: Identify each gamble's worst outcome. Then choose the gamble with the lowest probability of the worst outcome.
- **Most likely**: Identify each gamble's most likely outcome. Then choose the gamble with the highest, most likely outcome.

Using the rules of each heuristic, predictions of choices can be made for every decision problem (pair of gambles).

3. Conducting research and results

3.1. Experimental design and data collection

The data were obtained from an incentivized experiment involving binary choices under risk. The experimental study was conducted in the laboratory at the University of Gdansk. The participants were undergraduate students who volunteered for the survey. The average age of the participants was 21, and approximately 64% of them were women.

The data collection began with one training session, followed by six sessions spaced one week apart. In each session, participants were presented with 63 decision problems, each involving two lotteries. The sets of decision problems remained consistent within each session but varied across sessions. Some problems were repeated in certain sessions. The stimuli design for the decision problems was constructed based on the HILO structure (Camerer, 1995), as well as the studies conducted by Loomes and Sugden (1998) and Harrison and Swarthout (2016). The design assumed that the output domain ranged from -100 zł (Polish zloty) to 100 zł, with increments of 10 zł (approximately 2.2 euros). A complete list of the lotteries, including information on which pairs of lotteries were presented in each session, is available online (https://zenodo.org/record/8102028).

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Out of the recruited 77 subjects, 73 participated in at least 4 sessions (56 subjects completed 6 sessions, 16 completed 5 sessions, and 1 subject completed 4 sessions). The total number of choices analyzed amounted to 26,500, considering the data from these 73 subjects. The majority of participants needed less than half an hour to complete each session.

Decisions were presented in a standard game format, where each decision problem involved choosing between two presented lotteries. The print screen of the choice presentation format (originally in Polish) are shown in the Figure 2.

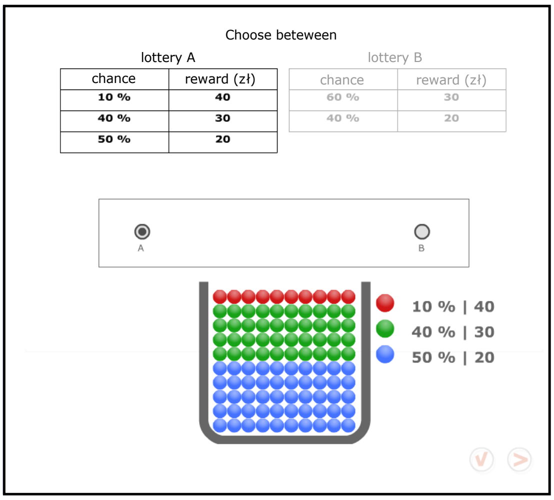

Figure 2. Format of the presentation of decision problem in the experimental study
Source: *own elaboration*

Three types of lotteries were used: positive, negative, and mixed lotteries (21 of each type of decision problem in each session). To control for the effect of experienced gain or loss, the order of presenting each type of decision problem was fixed. Participants encountered decision problems in a specific sequence: positive, followed by negative, and then mixed, repeated in 7 sequences. The order of displaying decision problems of each type was fixed across participants (each participant received decision problems in the same order).

The experimental design included immediate feedback. After each choice, the chosen lottery was played using an animation presenting an urn with 100 colored balls, representing the lottery's distribution. The draw of the ball was then animated, and the resulting outcome of the choice was presented on the screen. Therefore, after each choice, subjects learned the results of their choices, but no sum or balance of all the choices' results was presented. The experiment was conducted using a custom-made application programmed specifically for the purpose of this study.

The incentives system applied to all types of games, including gain, loss, and mixed lotteries. Therefore, subjects experienced both wins and losses. At the end of each session, four decision problems were randomly selected for payment, consisting of two positive, one negative, and one mixed lotteries' game. Participants were informed about the selected decision problems, and the results of these four choices were displayed and added to the subject's reward balance. The unequal distribution of rewarded game types (2 gains - 1 loss - 1 mixed) was intended to ensure that all subjects, on average, earned at least a reward that covered their time cost. All in all, participants could not incur losses in the experiment as it would be unethical to allow subjects to gamble and risk their personal funds in an experimental study. The resulting rewards for the subjects ranged from 90 zł to 420 zł, with an average value of 242 zł (approximately 55 euros).

3.2. Results: risk attitudes

To assess the participants' approach to risk, we examined their willingness to take risk when choosing from pairs of lotteries. Since the majority of decision problems involved choosing between two lotteries, with rarely a certain payoff option available, we identified the risky lottery based on its dispersion, measured by the standard deviation (SD). When presented with two lotteries to choose from, the one with the higher SD was identified as the more risky option. If the participant selected the lottery with the higher SD, the choice was marked as a risky one.

Next, we analyzed the frequency of selecting risky options by comparing the proportions of risky choices among all the decisions made by the subjects. Overall, the risky option was chosen in 57.6% of situations, which can be assessed as high result. The percentage of risky choices for all types of lotteries across all six sessions is presented in Figure 3. Apart from the overall high level of risky choices, we observed variations in the results across sessions. To test the equality of proportions among the sessions, we conducted the chi-square test. The results of the test rejected the hypothesis of equal proportions, indicating that at least one of the proportions is different from the others ($\chi_5^2 = 56.04$, p-value < 0.001).

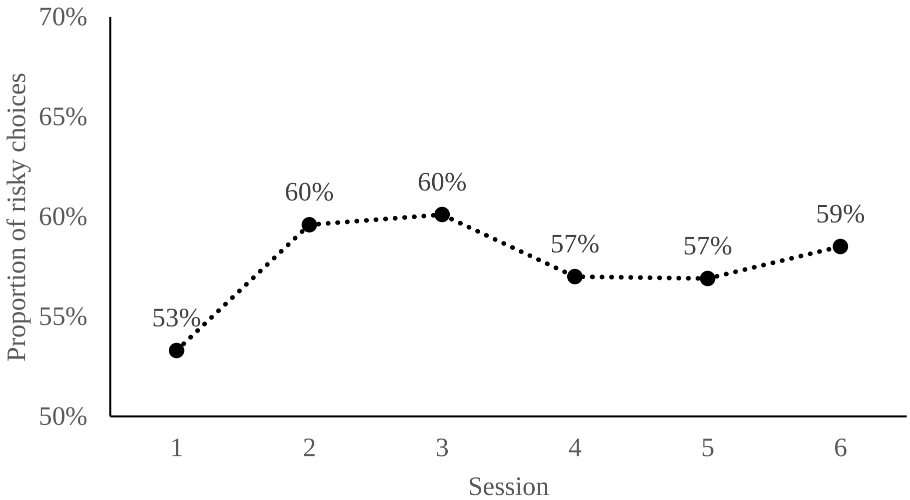

Figure 3. Overall risky choices across experimental sessions
Note: Lottery choices with a higher standard deviation are counted as risky ones.
Source: own data

Furthermore, we observed a significant increase in the percentages of risky choices between first and second sessions. Although the results fluctuated in successive sessions, the first session consistently showed the lowest proportion of risky choices of all sessions. This conclusion is supported by the results of the χ^2 test for trend in proportions ($\chi_1^2 = 6.18$, p-value $= 0.013$), which indicate a positive trend in the level of risky choices across experimental sessions and confirm Hypothesis 1.

We attribute these changes in risky choices to the presence of a learning effect. Participants not only gained experience in the first session but also had the opportunity to evaluate the quality of their decisions through the immediate feedback they received.

To test the confirmation of Hypothesis 2, we investigated the proportions of risky choices based on the type of decision problems. The consistent patterns of changes in risky choices across sessions is also visible in Figure 4, which displays the results by the type of decision problems: gain, loss and mixed. Within each of these problems, a clear increase in risky choices between the first and second sessions is observable. More importantly, in line with prior studies (Kahneman & Tversky, 1979), it is noteworthy that the gains decisions exhibit significantly lower frequency of risky choices compared to loss decisions. This finding holds true across all sessions.

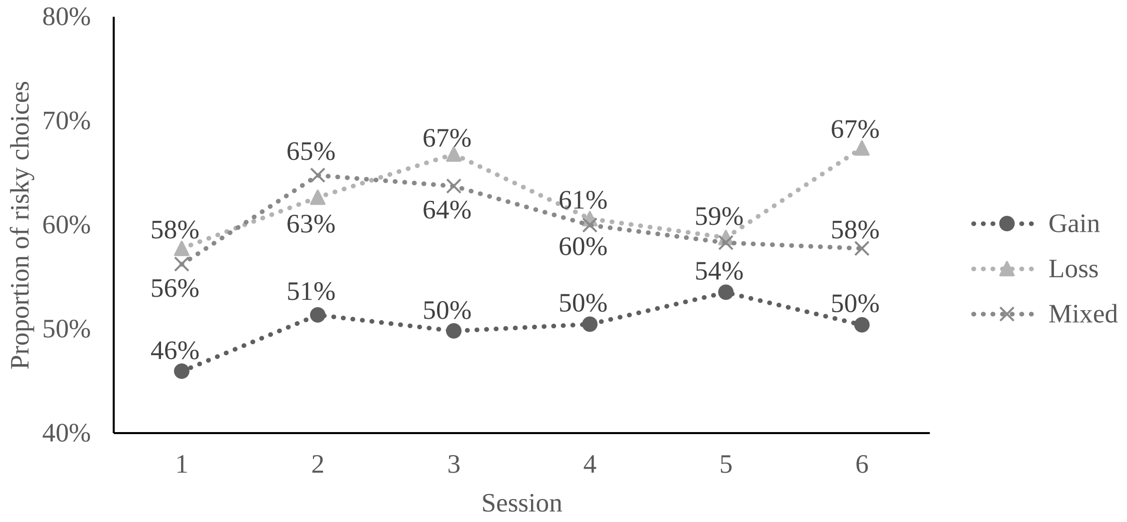

Figure 4. Risky choices in different types of lotteries across experimental sessions
Note: Lottery choices with a higher standard deviation are counted as risky ones.
Source: own data

To further assess the equality of proportions across decision types, a chi-square test was conducted. The test results indicate a significant difference between the proportions ($\chi_2^2 = 302.09$, p-value < 0.001), with proportions evaluated as 0.50 for gains, 0.62 for losses, and 0.60 for mixed lotteries. An additional test was performed to verify the significance of the difference between the proportion of risky choices in loss and mixed problems, results of which also confirms the significance of difference between this pair ($\chi_1^2 = 9.36$, p-value $= 0.002$). Overall, these results provide confirmation of Hypothesis 2.

Regarding mixed lotteries, it is worth noting that they have a higher overall frequency of risky choices compared to gain lotteries. However, contrary to both loss and gain conditions across all sessions, mixed problems do not exhibit such a consistent pattern. We attribute this outcome to the higher complexity of choice involved in the mixed lotteries. The construction of a mixed lottery, which contains both gains and losses, contributes to its increased complexity. Such complexity may play a role in the choice patterns observed.

3.3. Results: heuristics

In this part of the analysis, we predicted the choices for each decision problem by applying the rules of the heuristics described in Section 2.2. These rules were used to determine which lottery from each pair (i.e., decision problem) would be chosen if the participant followed a specific heuristic.

However, for some decision problems used in the experiment, certain heuristics were unable to differentiate and indicate the better lottery to choose. Only two heuristics, namely the priority and the least likely heuristics, consistently provided a definitive choice. The conclusiveness of each heuristic for the set of decision problems used in the experiment is presented in Table 1.

Table 1. Conclusiveness of heuristics prognosis for decision problems used in the experiment

Heuristics	Conclusive prognosis (in %)	Heuristics	Conclusive prognosis (in %)
Priority	100.0	Minimax	44.0
Equiprobable	76.8	Maximax	34.5
Equal weight	91.1	Lexicographic	47.6
Better than average	45.8	Least likely	100.0
Tallying	70.2	Most likely	48.8
Probable	59.5		

Source: *own elaboration*

The conclusiveness indicates the percentage of decision problems for which the heuristic clearly indicated which of the two lotteries is better to choose. The decision problems used in the experiment followed the HILO structure, which has been used in previous studies to test the expected utility model and investigate how prospect theory explains various choice anomalies, including the certainty effect, common ratio effect, common consequence effect, and more (Camerer, 1995; Loomes & Sugden, 1998; Starmer, 2000). However, some of the heuristics in our study were only able to give a conclusive prognosis for less than half of the problems in the HILO structure. This shows their limited applicability for predicting choices under risk.

Among the successful heuristics, besides priority and least likely, the equal weight (91.1%), equiprobable (76.8%), and tallying (70.2%) heuristics showed high conclusiveness. On the other hand, the minimax and maximax heuristics demonstrated the lowest conclusiveness, proving to be ineffective for this set of decision problems.

Next, we investigated the proportions of correct predictions using two different methods, which are presented on the left and right sides of Figure 5. The left-hand side of Figure 5 represents the results obtained by following the methodology of Glöckner and Pachur (2012), which evaluates correct predictions for all subjects' choices. On the other hand, the right-hand side of Figure 5 is based on the methodology of Brandstätter et al. (2006), which compares the heuristics' prognosis to the majority of choices for each decision problem.

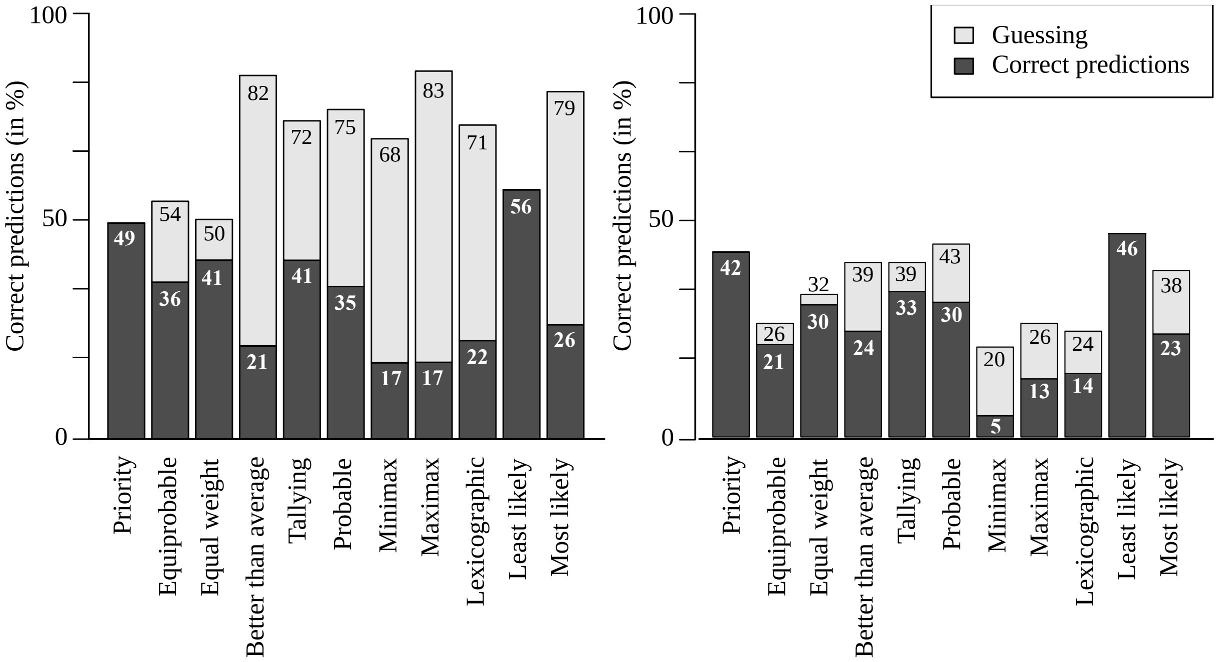

Figure 5. Correct predictions of the heuristics
Note: The figures depict results obtained using two different methods. The figure on the left displays the correct predictions evaluated for all subjects' choices, while the figure on the right shows the correct predictions evaluated for the majority of choices.
Source: *own data*

The Figure 5 presents two measures of predictiveness of heuristics: strict correct predictions and guessing. Strict correct predictions are indicated when the heuristic aligns with the lottery chosen by the subject (the majority of subjects), as shown in the left variant (the right variant, respectively). Additionally, the figure includes the guessing prognosis, which represents situations where the prognosis was not conclusive. In the subjects’ choice variant (left side of Figure 5) all such choices are reported, meaning that whatever the subject chose, it was in line with the heuristic “guessing” the choice. In the majority choices variant, guessing indicates cases where the lottery was inconclusive, and there was no clear majority of choices. Specifically, the proportion of choosing one of the lotteries in the particular problem did not differ significantly from 50%, as determined by a z-score test at a significance level of 0.05.

In general, the performance of the heuristics in our experimental data is low. One reason for this result is the high level of inconclusiveness exhibited by some heuristics for this set of decision problems. In both methodological approaches, the most effective heuristic was the least likely, which recommends selecting the gamble with the lowest probability of the worst outcome. The priority heuristic, which employs a more complex sequence of reasoning, takes second place in the heuristic ranking. The results obtained using the majority choices prognosis (right side of Figure 5) suggest slightly worse performance of the heuristics. Particularly, the low scores on the guessing prognosis for the majority of choices indicate that subjects were not indifferent between the pairs of lotteries where the heuristics were inconclusive. In other words, the majority of choices favored one of the lotteries, while the heuristic was unable to make a decision. The relatively small bars representing guessing indicate situations where the heuristic correctly identified the subjects' indifference.

Another reason for the low performance of the heuristics is the effect of immediate feedback implemented in the experimental design. As shown in the previous section, participants in the immediate feedback condition demonstrated an inclination towards taking risks, which contradicts the risk-value tradeoff. This tradeoff, which assumes that risk is an undesirable feature of the lottery, is used in the construction of heuristics. Consequently, when participants made riskier choices, they deviated from the heuristics that were intended to guide them towards safer choices.

To investigate the validity of Hypothesis 3, we compared the performance of heuristics (correct predictions) based on the type of decision problem. Figure 6 presents the variability in correct prognosis across heuristics for gain, loss, and mixed decision problems. Correct predictions were evaluated for all subjects' choices, including the guessing prognosis (0.5 of such prognoses were included). The dotted lines connecting the points do not indicate dynamics; they are solely used to aid in locating the results of the same type of decision problem.

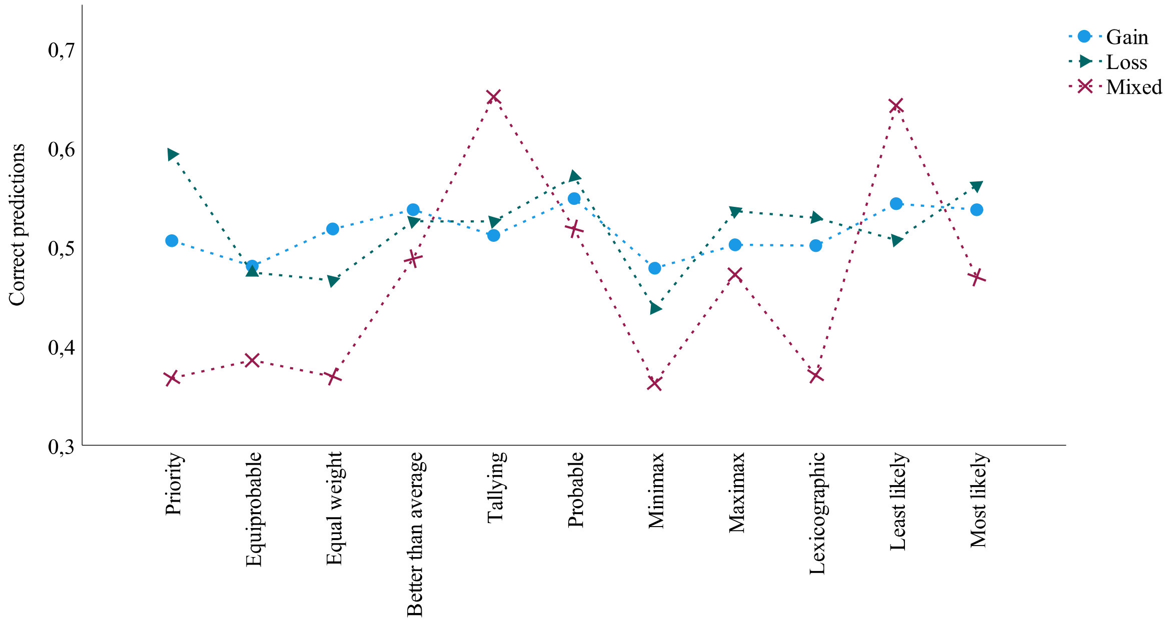

Figure 6. Correct predictions of the heuristics by decision problem type
Note: Correct predictions were evaluated for all subjects' choices, including the guessing prognosis (0.5 of such prognoses were included).
Source: *own data*

In general, there is a significant difference in correct prognosis among decision types for most heuristics. However, the heuristics better than average, probable, and maximax demonstrated prognoses that were around chance for all types of problems.

Most variability in heuristics correct prognosis can be observed for mixed problems, where two heuristics, tallying and least likely, outperform the others. It appears that these two heuristics are particularly useful when dealing with complex problems. Priority heuristic, which performed the best prognosis for loss decision problems, performed the worst for mixed problems. For the gain decision problems all heuristics prognosed around chance, with the probable heuristic slightly outperforming the others.

On average, the heuristics that incorporated both outcome and probability information performed better across all types of lotteries compared to outcome-oriented heuristics. While none of the heuristics can be identified as the rule followed by the majority of subjects, we can confidently reject the notion that subjects neglected probability information. Considering all the findings, it can be concluded that the subjects incorporated both probability and outcome information in their decision processes.

Conclusion

The study aimed to investigate decision-making behavior under risk using a repeated choices experimental design with immediate feedback. The choices made by participants were analyzed to assess the effectiveness of various heuristics in predicting their decisions. The findings indicated that participants, in the presence of immediate feedback, displayed a high willingness to take risks, consistent with previous research suggesting an increase in risk-taking with experience. Notably, there was a significant increase in risky choices after the first session.

However, the overall performance of the heuristics in predicting the experimental data was relatively low. This can be attributed to the high inconclusiveness of certain heuristics for the decision problems employed in the experiment. Among the tested heuristics, the least likely heuristic consistently outperformed others, indicating a preference for lotteries with the lowest probability of the worst outcome. The priority heuristic, which involves a more complex reasoning process, also showed relatively better performance. In contrast, the minimax heuristic performed poorly across all performance measures and decision problem types.

The performance of the heuristics varied across different types of decision problems, with significant differences observed in correct prognosis among decision types. The complexity of decision problems, particularly in mixed lotteries, influenced the effectiveness of the heuristics. Tallying and least likely heuristics proved to be more helpful in dealing with mixed lotteries.

The study provides insights into the limitations and challenges associated with using heuristics in decision-making when immediate feedback is provided. It emphasizes the need for further research to enhance the applicability and performance of heuristics in various decision-making contexts.

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