AARHUS BSS SCHOOL OF BUSINESS AND SOCIAL SCIENCES AARHUS UNIVERSITY

ESSAYS ON RISK-TAKING AND EXPLORATION-EXPLOITATION BEHAVIORS

PhD dissertation

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Preface

This dissertation has been written between February 2019 and March 2021, during my enrollment as a Ph.D. student at the Department of Economics and Business Economics at Aarhus University. This journey has been extremely enriching and, at the same time, full of ups and downs.

A lot of people deserve very special thanks. Hence, I would like to sincerely thank my supervising team, Professor Alexander Koch and Associate Professor Dan Mønster. This dissertation would not have been the same without their support. And great thanks to my family and especially my Mom 'Mahnaz' for their continued support, encouragement, and endless love and also my friends for believing in me and being always there for me.

The pre-defense meeting was held on May 19, 2021. I am grateful to the members of the assessment committee consisting of Professor Stephan Billinger (SDU, Denmark), Professor Sebastian Wallot (Leuphana University, Germany), and Associate Professor Carsten Bergenholtz (AU, Denmark) for their careful reading and their insightful comments and suggestions. Some of the suggestions have been incorporated into the present version of the dissertation, while others remain for future research.

Fatemeh (Arezoo) ShahrabiFarahani

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Contents

Summary

This thesis consists of three independent chapters that contribute with insights into areas of human decision-making. The first chapter focuses on risk-taking behavior, while the second and third chapters are focused on exploration-exploitation. Thus, one object of interest in all chapters is to shed light on features in decision-making behavior. The first chapter compares different factors and tests their effect on risk-taking, while the second and third chapters use process tracing tools to shed light on dynamics of behavior.

All chapters are based on experimental data which has been collected through controlled experiments in laboratories. Data for these chapters was collected in the Aarhus University Cognition and Behavior Lab facilities.

The first chapter is entitled 'Effects of different levels of uncertainty and social interactions on risk-taking and information gathering' and investigates risk-taking behavior in a 2 × 2 between-subject design using two levels of uncertainty and interactions. Here two levels of uncertainty have probabilistic information about the outcome' risk,' and incomplete information' ambiguity' [1,2] is investigated. Besides uncertainty, the situation of making a decision is also critical as people have always been inclined to look to others in uncertain situations for getting advice or learning from them to decrease their uncertainty [3,4]. These interactions leave them remarkably vulnerable to be influenced by others' opinions and behaviors [3,4]. Thus, this aspect is also tested with two levels of social and individual manners. All these conditions are implemented in the laboratory using a computer decision-making experiment. Results indicate that risk-taking is higher in social ambiguity than in social risk. It results from a lack of information in this context with the possibility of being affected by others' decisions.

The second chapter, 'Exploration-Exploitation Flow in Choice and Visual Sampling', deals with the exploration-exploitation trade-off in two modalities. Unlike in previous studies which categorized visual exploration according to the chosen option in a choice task [5–7], this study collects both aspects individually in two separate tasks rather than measuring them independently to have a true measure of visual exploration. One task is the famous two-armed bandit task [8], and the other is a new setup for visual exploration-exploitation. Using two tasks in a within subject design, this study compares participants' exploratory behavior in choice and visual sampling. Hence these two tasks are unrelated in appearance, but both measure the same

thing. Results show a positive relation between exploration in both tasks with a higher exploration rate in the visual task.

The third chapter, 'The Dynamics of Decision-making in an Exploration-Exploitation Paradigm', investigates exploration-exploitation dynamics using two outcomes of our inference system, 'attention' and 'action'. Eye and hand movements are collected in this study to account for these behaviors [9–11]. Eye and hand movements are initiated by anatomically separate regions in the brain, and depending on the need these movements can be coupled and decoupled [10]. Using eye and hand movements, data was collected from the bandit task of the previous paper. The relation of these two behaviors is examined in exploration-exploitation behavior as both time series have non-linear characteristics; their relation is tested using a related technique of measuring synchrony in data. The Cross Recurrence Quantification (CRQA) [12] technique is used here to reach this aim. Results showed that while participants are exploiting, they are more sure about their choices and have higher synchrony in their eye-hand movements, while they are lower in certainty and synchrony during exploratory behavior.

References

1. Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., & Camerer, C. F. (2005). Neural systems responding to degrees of uncertainty in human decision-making. *Science*, *310*(5754), 1680–1683.

2. FeldmanHall, O., Glimcher, P., Baker, A. L., & Phelps, E. A. (2016). Emotion and decision-making under uncertainty: Physiological arousal predicts increased gambling during ambiguity but not risk. *Journal of Experimental Psychology: General*, *145*(10), 1255.

3. Qi, S., Footer, O., Camerer, C. F., & Mobbs, D. (2018). A collaborator's reputation can bias decisions and anxiety under uncertainty. *Journal of Neuroscience*, *38*(9), 2262–2269.

4. Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, *357*(4), 370–379.

5. Stojić, H., Orquin, J. L., Dayan, P., Dolan, R. J., & Speekenbrink, M. (2020). Uncertainty in learning, choice, and visual fixation. *Proceedings of the National Academy of Sciences*, *117*(6), 3291–3300.

6. Ehinger, B. V., Kaufhold, L., & König, P. (2018). Probing the temporal dynamics of the exploration–exploitation dilemma of eye movements. *Journal of Vision*, *18*(3), 6–6.

7. Walker, A. R., Luque, D., Le Pelley, M. E., & Beesley, T. (2019). The role of uncertainty in attentional and choice exploration. *Psychonomic Bulletin & Review*, *26*(6), 1911–1916.

8. Banks, J., Olson, M., & Porter, D. (1997). An experimental analysis of the bandit problem. *Economic Theory*, *10*(1), 55–77.

9. Schulte-Mecklenbeck, M., Kühberger, A., & Ranyard, R. (2011). The role of process data in the development and testing of process models of judgment and decision making. *Judgment and Decision Making*, *6*(8), 733.

10. Horstmann, N., Ahlgrimm, A., & Glöckner, A. (2009). *How distinct are intuition and deliberation? An eye-tracking analysis of instruction-induced decision modes*. Preprints of the Max Planck Institute for Research on Collective Goods.

11. Barca, L., & Pezzulo, G. (2015). Tracking second thoughts: Continuous and discrete revision processes during visual lexical decision. *PloS One*, *10*(2), e0116193.

12. Coco, M. I., & Dale, R. (2014). Cross-recurrence quantification analysis of categorical and continuous time series: An R package. *Frontiers in Psychology*, *5*, 510.

Danish summary

Resumé

Denne afhandling består af tre uafhængige kapitler, der bidrager med indsigt i dele af beslutningstagningsprocessen hos mennesker. Første kapitel fokuserer på risikovillig adfærd, mens andet og tredje kapitel fokuserer på udforskning vs. udnyttelse. Et fokuspunkt i alle kapitler er således at kaste lys over detaljer ved beslutningstagningsadfærd. I første kapitel sammenlignes forskellige faktorer, og deres virkning på risikovillig adfærd undersøges, mens andet og tredje kapitel bruger processporingsværktøjer til at kaste lys over adfærdsdynamikken.

Alle kapitler er baseret på eksperimentelle data, som er indsamlet gennem kontrollerede eksperimenter i laboratorier. Data brugt i disse kapitler blev indsamlet i Aarhus Universitets 'Cognition and Behavior Lab'-faciliteter.

Det første kapitel har titlen 'Effects of Different Levels of Uncertainty and Social Interactions on Risk-taking and Information Gathering' og undersøger risikovillig adfærd i et 2 × 2 between-subject design ved hjælp af to standarder for usikkerhed og interaktioner. Her giver de to standarder for usikkerhed sandsynlige oplysninger om udfaldets risiko, og tvetydigheden ved mangelfuld kommunikation [1,2] undersøges.

Beslutningstagnings-situationen er ud over at være usikker også kritisk, fordi mennesker altid har været tilbøjelige til at aflæse andre i usikre situationer for at få råd eller lære af dem for at mindske egen usikkerhed [3,4]. Disse interaktioner efterlader beslutningstagerne bemærkelsesværdigt sårbare over for at blive påvirket af andres meninger og adfærd [3,4]. Derfor testes også dette aspekt med to standarder for hhv. social og individuel opførsel. Alle disse betingelser implementeres i laboratoriet ved hjælp af et beslutningseksperiment på computer. Resultaterne indikerer, at risikovillighed er højere ved social tvetydighed end ved social risiko. I denne sammenhæng skyldes det mangel på information samt muligheden for at blive påvirket af andres beslutninger.

Andet kapitel, 'Exploration-Exploitation Flow in Choice and Visual Sampling', handler om afvejning af udforskning vs. udnyttelse i to modaliteter. I modsætning til tidligere undersøgelser, der kategoriserede visuel udforskning ud fra den valgte mulighed i en valgopgave [5–7] snarere end at måle dette uafhængigt for at have et præcist mål for visuel udforskning, måler denne undersøgelse begge aspekter individuelt i to separate opgaver.

Den ene opgave er den berømte to-armede tyveknægt-opgave [8], og den anden er et nyt set-up med henblik på måling af visuel udforskning vs. udnyttelse. Ved hjælp af to opgaver i et between-subject design sammenligner denne undersøgelse deltagernes udforskende adfærd inden for valg og visuel afprøvning. Derfor ligner disse to opgaver ikke hinanden, men begge måler det samme. Resultaterne viser en positiv sammenhæng mellem udforskning i begge opgaver med en højere udforskningshastighed i den visuelle opgave.

Det tredje kapitel, The Dynamics of Decision-making in an Exploration-Exploitation Paradigm', undersøges dynamikken i hhv. udforskning og udnyttelse ved hjælp af to resultater fra vores inferenssystem, 'opmærksomhed' og 'handling'. Øjen- og håndbevægelser indsamles i denne undersøgelse for at kunne redegøre for denne adfærd [9–11]. Øjen- og håndbevægelser initieres af anatomisk adskilte regioner i hjernen, og afhængigt af behovet kan disse bevægelser sammenkobles og frakobles [10]. Data blev indsamlet fra tyveknægtsopgaven i det foregående kapitel ved hjælp af øjen- og håndbevægelser.

Forholdet mellem disse to slags adfærd undersøges som en del af udforskning vs. udnyttelsesadfærd, da begge tidsserier har ikke-lineære karakteristika, og deres forhold testes ved hjælp af en teknik relateret til måling af synkronisering i data. Cross Recurrence Quantification (CRQA) [12]-teknikken bruges her til at nå dette mål. Resultaterne viste, at når deltagerne udnytter, er de sikrere på deres valg og har højere synkronisering i deres øjen-/håndbevægelser, mens de er mere usikre og har lavere synkronisering ved udforskende adfærd.

Litteratur

1. Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., & Camerer, C. F. (2005). Neural systems responding to degrees of uncertainty in human decision-making. *Science*, *310*(5754), 1680–1683.
2. FeldmanHall, O., Glimcher, P., Baker, A. L., & Phelps, E. A. (2016). Emotion and decision-making under uncertainty: Physiological arousal predicts increased gambling during ambiguity but not risk. *Journal of Experimental Psychology: General*, *145*(10), 1255.
3. Qi, S., Footer, O., Camerer, C. F., & Mobbs, D. (2018). A collaborator's reputation can bias decisions and anxiety under uncertainty. *Journal of Neuroscience*, *38*(9), 2262–2269.

4. Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, *357*(4), 370–379.

5. Stojić, H., Orquin, J. L., Dayan, P., Dolan, R. J., & Speekenbrink, M. (2020). Uncertainty in learning, choice, and visual fixation. *Proceedings of the National Academy of Sciences*, *117*(6), 3291–3300.

6. Ehinger, B. V., Kaufhold, L., & König, P. (2018). Probing the temporal dynamics of the exploration–exploitation dilemma of eye movements. *Journal of Vision*, *18*(3), 6–6.

7. Walker, A. R., Luque, D., Le Pelley, M. E., & Beesley, T. (2019). The role of uncertainty in attentional and choice exploration. *Psychonomic Bulletin & Review*, *26*(6), 1911–1916.

8. Banks, J., Olson, M., & Porter, D. (1997). An experimental analysis of the bandit problem. *Economic Theory*, *10*(1), 55–77.

9. Schulte-Mecklenbeck, M., Kühberger, A., & Ranyard, R. (2011). The role of process data in the development and testing of process models of judgment and decision making. *Judgment and Decision Making*, *6*(8), 733.

10. Horstmann, N., Ahlgrimm, A., & Glöckner, A. (2009). *How distinct are intuition and deliberation? An eye-tracking analysis of instruction-induced decision modes*. Preprints of the Max Planck Institute for Research on Collective Goods.

11. Barca, L., & Pezzulo, G. (2015). Tracking second thoughts: Continuous and discrete revision processes during visual lexical decision. *PloS One*, *10*(2), e0116193.

12. Coco, M. I., & Dale, R. (2014). Cross-recurrence quantification analysis of categorical and continuous time series: An R package. *Frontiers in Psychology*, *5*, 510.

CHAPTER **1**

Effects of Different Levels of Uncertainty and Social Interactions on Risk-taking and Information Gathering

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Abstract

This study examines the effect of being or not being exposed to social interactions and the level of uncertainty faced by decision-makers on risk-taking and information gathering. A 2 × 2 between-subject design is used which shows whether the situation is one of risk or ambiguity (uncertainty dimension), and whether the decision is taken individually or affected by other participants' decisions (social dimension). Results indicate that risk-taking is higher in social ambiguity than in other groups. However, there is no effect on information gathering, which is the amount of information gathered about the choices made by other group members. The variation in risk-taking results from a difference between participants' scores and others' maximum scores, since participants can also see each other's scores. This means that the more significant this difference, the greater the willingness to take risks.

Keywords: Risk-taking, Uncertainty, Risk, Ambiguity, Individual, Social, Behavior

1.1 Introduction

There are different definitions of risk-taking depending on the context and perspective of the investigator. Yates[1] provides a comprehensive definition that "Risk-taking is any consciously, or non-consciously controlled behavior with a perceived uncertainty about its outcome, and/or about its possible benefits or costs for the physical, economic or psycho-social well-being of oneself or others" [1]. Based on the risk-sensitivity theory, organisms take the risk to achieve their goals which are typically out of reach through safe means [2]. Foraging and competition for mates are examples of this [1,2]. Evaluation of the outcome probabilities plays an important role in the context of risk-taking [3–6].

The knowledge of the outcome could be certain; when the outcome has the highest probability and surely happens (almost 100% of the time), or uncertain, which contains two categories [7].

Risk and ambiguity are the categories of the situations in which the decision-maker may face uncertainty [3,8–12]. In decisions under risk, probabilities of different outcomes are known or at least subjectively fixed, whereas, in decisions under ambiguity, this is not the case, because important information is missing or conflicting [3,8–10,12]. As an example, the probability of any outcome on a roulette wheel is known. However, it is not so straightforward to put probabilities on a particular type of terrorist attack occurring [13].

It is noteworthy to add that this basic distinction goes by many names. Some disciplines use "uncertainty" instead of "ambiguity" [12,14,15]. Some "unambiguous" vs. "ambiguous" probability (Ellsberg, 1961); "precise" or "sharp" vs. "vague" probability (Savage, 1954, p. 59), "epistemic reliability" (Gardenfors and Sahlin, 1982), and so forth [16].

Some disciplines use uncertainty as an umbrella term that contains risk and ambiguity as different levels of uncertainty [3,4,9,11], similar to what we are using here. When these two categories come together, as what Ellsberg suggested in his ambiguity aversion theory [12,17], people tend to prefer options with known probabilities (risk) to those with unknown probabilities (ambiguity) [4,18–20]. It shows violations of the postulates in Savage (1954) that two events should be treated equally as the same probability weight is assigned to them [21]. Ellsberg argued that these violations might be related to the ambiguity of information, which is defined as "a quality on the amount, type, reliability and 'unanimity' of information giving rise to one's degree of 'confidence' in an estimate of relative likelihoods."[21].

Decision maker's preferences on these uncertain situations can be defined by the outcome together with the belief about that outcome, which is the weights people attach to events (relative likelihood). The belief in the risky situation is objective and known, while it is subjective in the ambiguity [16]. It means that people consider existing known probabilities for options' outcomes in risk situations, while they use their subjective probabilities in ambiguity; thus, their responses are different toward these conditions [22–24]. The probability of gaining an outcome in a risk situation is known with zero variance, while it has higher variance in ambiguity which is also known as 'uncertainty about uncertainty' situation [25].

In this regard, Fujino et al. (2016) [4] ran an experiment similar to what Ellsberg did about selecting a red chip from two bowls with different distributions of the combination of red and blue chips. One bowl had 12 red and 12 blue chips (risky bowl), and the other had a mix of 24 red and blue chips (ambiguous bowl). Results showed that most of the participants chose the risky bowl, which suggests that people prefer to avoid ambiguous situations in favor of equivalent risky ones, and the purely objective bet is preferred to the subjective one [26], which is known as ambiguity aversion. This highlights the role of information in reducing ambiguity [27].

However, ambiguity aversion is sensitive to the context and domain of the decision-making [28]. As Chow et al. (2001) showed, in a non-comparative context where a person is faced with an ambiguous or unambiguous situation separately, ambiguity aversion disappears [29].

People are unwilling to decide in uncertain situations and try to enhance their lack of information through learning from context or others [27,30]. They explore more to learn as much as possible about the information distribution in order to reduce their uncertainty

[31]. Mentioned study investigated behavior in four medical search heading interfaces using the eye-tracking device. They differed in terms presented to figure out how participants search for patches of information [31]. Wittek et al. (2016) [31] showed that exploitative behavior is a response to risk, as uncertainty can be reduced by exploiting and understanding one known option better. However, exploratory behavior is a response to ambiguity with the aim of having a higher outcome somewhere else [31].

This behavior is explained by uncertainty reduction theory (URT), which states that high levels of uncertainty result in information seeking and, as communication increases, the level of uncertainty decreases [19]. Based on the URT, experiencing uncertainty leads to information seeking as a means to control the situation [32–34]. This is borrowed from the context of interpersonal communication, and it suggests that uncertainty motivates people to seek information to reduce it [19].
Interpersonal communications make it probable that decision-makers reshape their behaviors, and similarly, risk-preference can also be modulated by observing risky behavior in other agents and learning from their risk-related decisions [32–37]. The findings of the studies that investigate the social influence on risk-taking have mixed results [37]. Some studies showed facilitation in risk-taking [32] and some no effect of social exposure [35]. An example from the literature is the study by Brunette, Cabantous and Couture [38], who investigated group shift when alone, in a group, with risk, and in ambiguous conditions generated by a majority rule and a unanimity rule. They studied the impact of making decisions as part of a group environment on individuals' attitudes towards both risky and ambiguous prospects.

In a within-subject design, participants faced a series of multiple-choice lists asking to choose between certain and risky or certain and ambiguous conditions in a multiple price list task. Individuals had to make choices alone and as part of a three-person group. The researchers found that a group environment decreases individuals' degree of risk and ambiguity aversion, and individuals who belong to a group with unanimity rule are less risk-averse than individuals who belong to the majority rule [38].

The so-called social interaction effect indicates that noticing a peer choosing a risky option increases the agent's motivation to choose the risky option as well [39]. Several studies found that belonging to a similar group impacts people to behave similarly in risky environments [39,40]. Suzuki et al. (2016) [39] investigated the role of a contagion effect in modulating risk-taking behavior, using an experimental condition where participants could accept/reject a risky gamble over a guaranteed option after observing the choice of others. Tomova and Pessoa's [40] study confirms this in a setting where risk-taking is defined by the number of times that participants pump a balloon. With each pump, the chance increases of the balloon exploding, but the payoff increases if it does not explode. They played the game with three artificial participants to earn as much money as possible for the whole team. In each round, real participants first decided how many pumps they wanted to inflate. After they saw the choices of the artificial participants, they could change their previous choice. Tomova and Pessoa [40] found that observing more risky choices of others induced more risky choices while observing safe choices of others stimulated less risky choices.

Besides decision-making in a group environment, there are some real situations in life, such as shopping, in which we do not consider ourselves part of a group, but others' choices still affect us. Social contagion theory [41] posits that individuals in social relations are influenced by information dissemination, adoption of ideas, and spread of behavior [32,41–45]. In other words, individuals adopt the attitudes or behaviors of others with whom they communicate [41].

An example is a study by Scherer and Cho [46], who examined the impact of dyadic relationships on risk perception of water pollution in a rural community facing an environmental scare that potentially threatened its water supply. Individuals were asked to state their source of information about this context and the extent of their relationship with that source person. They answered a questionnaire about the risk of putting discharged water into their water supply. Results showed that the strength of the relationship between people was significantly related to the similarity of risk perceptions in the mentioned problem [46].

Regarding these studies, we already know that all else equal, people prefer a situation of risk over one of ambiguity. However, the two types of situations might lead to different risk-taking patterns and information search in a social context, which is not investigated yet.

In this study, we will investigate the combination of the theories of ambiguity aversion [12,17], Uncertainty Reduction Theory (URT) [34], and their effect on risk-taking behavior and interaction. We expect to see different desirability of risk-taking regarding the condition. As ambiguity aversion suggests, people feel more convenient and safer when choosing options that contain risk rather than the options with ambiguity. Knowing outcome probabilities will give them more confidence to choose options with higher risks. Thus, we will test the hypothesis that people in individual risk conditions take more risks than individual ambiguity (**Hypothesis 1**).

As mentioned, based on ambiguity aversion theory, people prefer to choose safer options with lower risks. Having the opportunity to interact with others reduces people's uncertainty and makes them more prone to choose options with higher risks compared to individual conditions. However, as in social risk, there is no need for more information to reduce uncertainty as outcome probabilities are already known, and participants use objective expected utility for their likelihood estimation. It is expected to see no difference between social and individual groups, and we will test it in hypothesis 2.1 (**Hypothesis 2.1**).

On the other hand, the outcome in social ambiguity is subjective and unknown which makes participants seek more information through social interactions. This not only makes them prone to create more interaction, but also makes them more affected by social information. Thus, we expect to see people take more risks as they reduce their uncertainty by the information coming from others, while in individual ambiguity conditions, people are more risk-averse as their subjective expectation doesn’t change because of social relations. It is expected that social relations increase the subjective expected utility of the chosen option, and thus participants make more risky choices in social ambiguity versus individual ambiguity (**Hypothesis 2.2**).

As mentioned, in social conditions, there is a possibility to decrease uncertainty by interacting with others in order to use social information. We test the hypothesis that participants make more interactions in the social ambiguity condition than in the social risk condition due to the information deficit in the former (**Hypothesis 3**).

To investigate the above-mentioned hypotheses, we designed a new choice task that enables us to compare risk-taking in equivalent experimental condition for ambiguity, risk, individual and social conditions. These experimental conditions consist of choosing a color from different color cards with different risk levels implied by choice. Both risk and ambiguity cases were run in a similar framework, but with different information about the color cards' distribution.

A great extent of social studies has been done when participants benefit as group members [32,36,39,41,46]. In this study, to investigate the peer effects without the possible confound of a group reward, participants' choices determine their individual payoff instead of being rewarded as a group.

1.2 Method

In this study, we investigate risk-taking using a 2×2 between-subjects design that varied depending on whether a choice task was performed in a social context or not, and whether the environment was characterized by risk or ambiguity. Each condition of the task was performed 50 times.

Specifically, in the *risk condition*, the probability distribution of the outcomes was provided to the participants, while in the *ambiguity condition*, it was not. In the *social condition*, there was a possibility of accessing information about other participants' choices (their score and earnings), whereas this option was not present in the *individual condition*. After finishing the task, participants answered the Domain-Specific Risk-Taking questionnaire (DOSPERT) [47].

1.2.1 The choice task

Participants were asked to guess a card's color in each condition, and it was to be drawn by the computer from six colors (orange, yellow, blue, red, green, purple)[1]. The total number of cards that the computer chose from was 60. This number was chosen in order to have the same number of cards for each color in the risk condition. That is, in this condition, there were 10 cards of each color (10 orange, 10 yellow, 10 blue, 10 red, 10 green, 10 purple), but in the ambiguity conditions, the number of cards for each color category was not identical (15 orange, 7 yellow, 9 blue, 10 red, 14 green, 5 purple).

[1] Color preferences could affect first trials in that decision making is random, but after passing some trials in which distribution of colors is important, it would not be rational not to choose a specific color because one doesn't like it, as it may have a high probability of winning (more investigation is presented in the discussion).

Thus, there was uncertainty about the distribution in the ambiguity situation, and the actual distribution was generically different from a uniform distribution. Participants did not have information about the number of cards in the ambiguous conditions, but they knew about the card distribution in the risk conditions. Thus, choice without replacement in risk conditions gave participants some clue about the number of remaining cards. There were two pre-randomized sequences of color draws (one for risk and one for ambiguity), so that choices could be directly compared across participants (cf. Appendix, computer colors subsection).

Participants could choose between several options that had different chances of being correct. As shown in Figure 1.1, there were four groups of choices available on the screen, containing different numbers of colors. Participants had to choose one option from all 24 possible choices (one-card circles, two-card circles, three-card circles, and four-card circles). Options differed in terms of the score when winning or losing. Winning was worth +1200 tokens if the guess on a one-card option was correct and −1200 when it was wrong. That is, one-card options had a win/loss score of ±1200. The win/loss score was ±600 for two-card options, ±400 for three-card options, and ±300 for four-card options. The options also differed in their chance of winning which tended to increase when moving away from the screen center. Choosing a one-card circle meant that the decision-maker took more risk by betting on only that color. For example, under the risk situation, the colors were initially uniformly distributed, such that a single-colored circle had a 1/6 chance of winning on the first draw of a color[2]. Choosing a circle with more colors tended to increase the chance of winning.

[2] Subsequent draws have different probabilities because draws were made without replacement.

Figure 1.1: An example of the task.

The risk involved with choices tends to decrease from the center (single-colored circles) to the outside (circles with four colors)

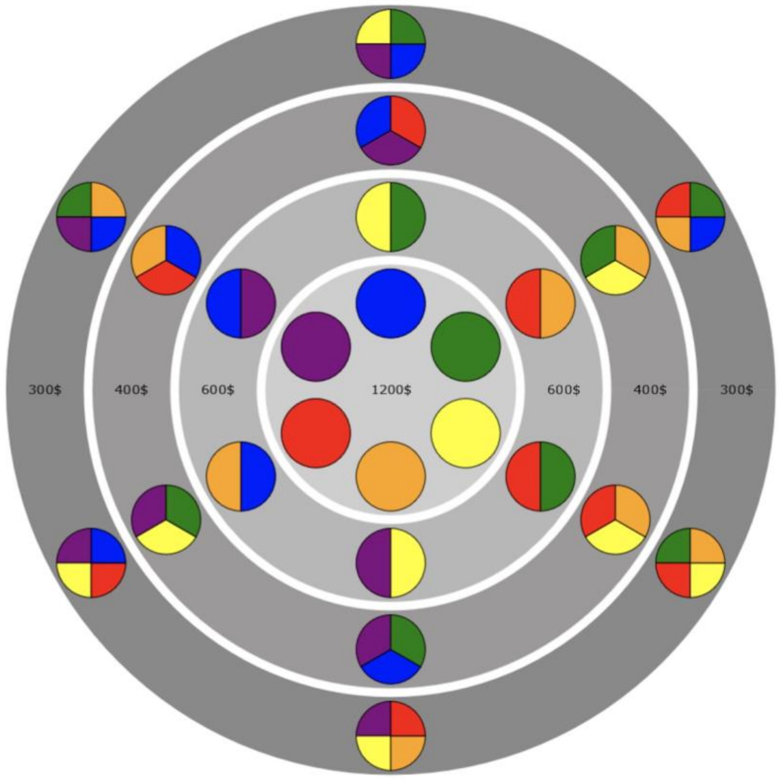


Table 1.1: The expected value of choosing the color circle groups for the first draw under a uniform distribution

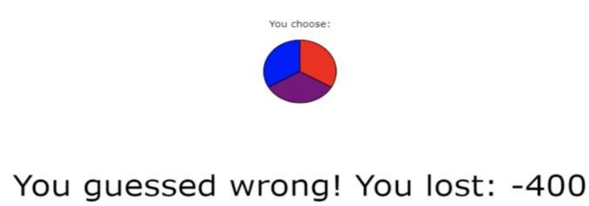
circles	expected value
one-card	$(1200 \cdot 1/6) - (1200 \cdot 5/6) = -800$
two-cards	$(600 \cdot 2/6) - (600 \cdot 4/6) = -200$
three-cards	$(400 \cdot 3/6) - (400 \cdot 3/6) = 0$
four-cards	$(300 \cdot 4/6) - (300 \cdot 2/6) = 100$

Specifically, on the first draw, the two-card options had a chance of winning 2/6, the three-card options had a chance of winning 3/6, and the four-card options had a chance of winning of 4/6. Table 1.1 shows the expected value for each group of circles for the first draw under a uniform distribution. Subjects performed the choice task 50 times. Each chosen card was replaced from the whole color-cards.

After each choice, the result was shown to the participants. If their guess was correct, they saw a message 'You guessed right! you earned: $$$', and if their guess was wrong, a similar message was shown to participants (cf. Figure 1.2). Each person could only find out the color of an actual card when her guess was correct and was from a one-color card group. Otherwise, in case of guessing right, two-color cards gave 50% chance, three-color cards gave 33%, and four-color cards gave 25% of finding out the actual color (it was not told to them directly). Thus, it is not straightforward to calculate if each choice's exact probability is affected by the previous choices.

Each round's chosen circle score, together with its expectation, indicated the risk-taking of the participants.

Figure 1.2: Screenshot of a message after a wrong choice



1.2.2 The social interaction choice (only relevant in the social conditions)

To provide conditions for uncertainty reduction, we offered participants with information from others about true card colors. No direct information was given to the participants about the true color of the computer card when they received feedback on their choice (Figure 1.2), except for one color cards in case of the true guessing.

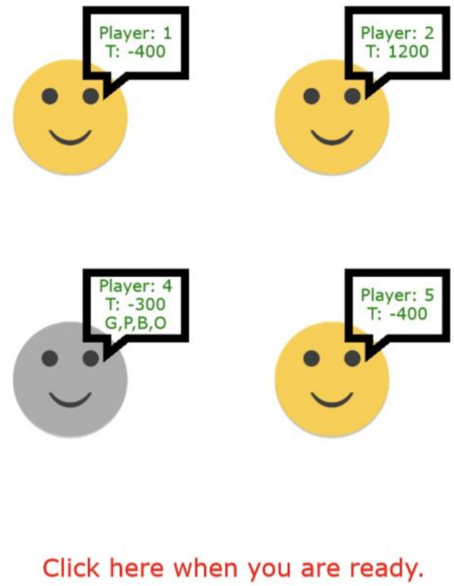
In the social conditions (social-risk and social-ambiguity), there were five participants in each social group. After finishing a choice task, each participant could see the other four people's outcomes and choices in the group for the previous round. They were represented using emojis (cf, Figure 1.3), next to which the score awarded to that participant for the previous choice round *T* was shown. The possible scores were ±1200, ±600, ±400, ±300. By clicking on each emoji, the corresponding participant's chosen option appeared as illustrated in Figure 1.3 with the abbreviated names of the chosen color. For example, from Figure 1.3, 'G,P,B,O' means that the selected player's choice was from groups of four colors: Green, Purple, Blue, and Orange, and that it was a wrong choice.

Each click changed the clicked emoji's color to gray and cost 10 tokens for the participant who clicked, subtracted from that round's score. That is, the outcomes were easily accessible for a participant with a small amount of effort and incurring a small cost. Looking at the participant's chosen option can give information about the true card color. Consequently, knowing the true color of each round, one can eliminate that color from the remaining cards on the computer. For example, from Figure 1.3, if someone clicks on an emoji with a score of 1200, it could be beneficial as she will find the true computer card which this person won with the positive score.

If it shows 'R', she can eliminate one from the remaining red cards she has in her mind. Clicks on emojis with lower scores could also be helpful regarding participants' previous choices. If she failed or succeeded by choosing a safer option with a low score and more colors, she can combine her chosen colors with the other person's to find out the true color. This information could help participants learn about distributing the colors of cards in the deck and reducing their uncertainty. There was no obligation or restriction in clicking on emojis.

Participants could choose as many emojis (participants) as they wanted, including none. The choice of whether or not to uncover details about others' decisions provides us with a measure of interaction to gain social information. Adding this possibility to the social information can affect participants' behavior which was investigated in this study.

Figure 1.3: The social interaction choice part of the task. The other four participants and their scores were shown. By clicking on a participant, their exact choice could be revealed at the cost of 10.



1.2.3 Questionnaire

In the last part of the study, participants answered the DOSPERT questionnaire [47]. It consists of 30 questions, each of which was rated using a 7-point Likert scale. Higher scores indicate greater risk-taking. This questionnaire is used to classify risk-taking in six sub-scales: ethical, financial, health/safety, recreational, and social. This allows us to control participants' risk-taking tendencies within and across conditions. Due to the similarity with the study's subject, the questionnaire's financial subscale was used here for the analysis. The reason behind collecting other sub-scales was to prevent bias in answering one specific sub-scale question.

1.2.4 Experimental procedure

Participants were randomly assigned to one of the condition groups. The number of participants in each session was related to the planned condition. For social conditions, each session had 5 participants. For individual conditions, up to 10 participants were assigned[3]. Participants sat at tables with dividers. Additionally, one table was left free in

[3] The limit reflected available physical space and the number of computers in the laboratory.

between participants to prevent them from talking to each other or seeing each other's choices. Participants were anonymous to each other[4]. At the beginning of a session, information about the task was given to the participants (see Appendix). Participants then had time to read the instructions and ask questions. The task was run for a total of 50 rounds[5]. Each trial was finished by choosing from the available options on the screen (Figure 1.1), followed by a screen showing the participants' scores, participants' choices, and successes or failures.

There was a social interaction choice after the choice task in the two social conditions (social risk and social ambiguity). In this, participants could see each others' scores for the current trial and optionally select to uncover the exact color of another participant's choice by clicking on the emoji for that participant (as shown in Figure 1.3). After finishing the 50 rounds, the final payment was calculated based on randomly selecting one of the scores for one trial out of the 50 trials. This kind of calculation ensured that participants had incentives to treat each choice as if it was the one that mattered. It avoided confounds that could arise if participants tried to hedge choices across rounds [48,49].

The selected score was converted to the final payment using an exchange rate of .037 DKK/point plus a show-up fee of 85 DKK and was shown on the screen. The worst-case scenario's possible score was −1240, and in the best-case, it was 1200. Payment ranged between 40 DKK and 130 DKK, and it was paid to the participants' bank account. The study was approved by the COBE Lab's Human Subjects Committee, and all participants provided written informed consent.

1.2.5 Participants

Participants were recruited from the subject pool of the Cognition and Behavior Lab at Aarhus University. A total of 114 subjects participated in the study. A session lasted 30 minutes on average, and the average earning was 85 DKK.

We needed to exclude 24 subjects from the analysis because of data missing due to a client-server disconnection. The remaining 90 participants were distributed with 25 in

[4] Participants were anonymous to each other in the task. They could not figure out which emoji belonged to which person when the experiment was running unless they talked to each other during the experiment, which was also forbidden and protected by the researcher.

[5] 50 rounds were selected to stop the experiment slightly before the time when choosing only one color card was rational.

social ambiguity (mean age = 24.0, standard deviation = 4.5, 17 female), 25 in social risky (mean age = 23.4, standard deviation = 3.3, 12 female), 23 in individual ambiguity (mean age = 23.6, standard deviation = 3.2, 14 female), and 17 in individual risk (mean age = 24.2, standard deviation = 3.9, 8 female).

1.3 Main Variables

To test the mentioned hypotheses, two variables of risk-taking score and interaction rate were measured as dependent variables. As it is a risk-taking study, factors of gender, age, self-reported risk-taking [32,33,50–54] and feedback [55–57] are considered to control their probable effect on the result. Because all the participants come from a similar age range (23.6 +/- 3.7), this factor is removed from analysis.

1.3.1 Dependent variable: Risk-taking score

There were four possibilities to investigate risk-taking in this study (chosen card group, round score (Variance risk-taking is defined as a preference for options with higher variances holding expected value (EV) constant), winning probability and expectation of the chosen option). However, these factors have some shortcomings. The first two variables were equivalent because both classified chosen options based on the card group's features. However, as the choice was without replacement in this study, these two variables can not express risk-taking adequately. There was no equal risk-taking between choosing one option from the one-card group in the first round with the other rounds. The win/loss probability of the choices was changed during the experiment. For example, in some late rounds, a one-color choice could have the same winning probability as a four-color option, and the one-color choice would be better because it has a higher reward. However, it is also riskier because it has a larger variance.

The expected value is calculated by multiplying possible outcomes by their related probabilities. There are studies that consider expected value for risk-taking [58] but others don't [59,60]. Considering the St. Petersburg paradox[6], it is a game with an infinite expected value, but rational people consider it risky and decide not to invest. This behavior is

[6] For more information about St. Petersburg paradox, see [60]

explained by portfolio selection theory, as this theory considers both expected payoff and variance. The portfolio selection theory was developed to capture the inability of single-parameter models to reflect multiple concerns of a decision-maker [61]. To explain the St. Petersburg paradox in this model: By increasing the expected payoff, the variance is also increasing, and it makes betting inefficient for larger payoffs [59,60].

For risk-averse decision-makers, the best option to choose is often the one with the highest expectation and the lowest variance [62]. The option with the highest mean and the lowest variance dominates any other feasible options and is classified as the safest [63]. To measure riskiness in this study, the number of dominated options associated with the selected option was calculated. Thus, each person has 50 values between 0 to 23 for each trial. For example, if one person had five options with higher expectations and lower variances than her selected option, her choice was dominated by five options. Her risk-taking score took the value of 5. It shows the number of better and safer options that the participant did not choose. The higher this value gets, the higher the risk-taking is.

Each group had a specific score related to the chosen circle group. This score can be positive when the guess was true, and negative the other way around. The scores were recorded during the experiment. In addition, each option had a probability of a win or loss regarding its trial (explanation will come later in this section). The expectation was measured for all participants (i) and all trials (t), as shown in Eq. 1. Score are depicted by $scoreW_{it}$ for win and $scoreL_{it}$ for loss. It is necessary to calculate each person's choice probability in every round as the choices were made without replacement, because it affects the number of remaining cards and also the overall results.

For calculating the probability, first, the number of cards in any chosen color was counted, and their related scores, which can be positive or negative depending on guessing right or wrong in that round, were recorded. Depending on this score, if a person's guess was true and the score was positive, and if the chosen option was from a one-color card, one was eliminated from the total number of that color. However, if the chosen option was from two-color cards, 1/2 was decreased from the total number of each selected color.

Similarly, for three-color cards 1/3 and for four-color cards 1/4 was decreased from each selected color's total number of cards. On the other hand, if the score was negative and the participant's guess was wrong about the actual color of the card, and if the chosen option was from one color card, 1/5 was eliminated from the total number of remaining colors. However, if the chosen option was from two-color cards, 1/4 was decreased from the total number of remaining cards.

Similarly, for three-color cards 1/3 and for four-color cards 1/2 were decreased from the remaining color's total number of cards. With this method, we calculate the probability for each persons' choice as a rational decision-maker. The number of cards in each color group for risk is 10, and ambiguity is unknown. The probability of loss ($probabilityL_{it}$) is calculated by subtracting the probability of win ($probabilityW_{it}$) over 1.

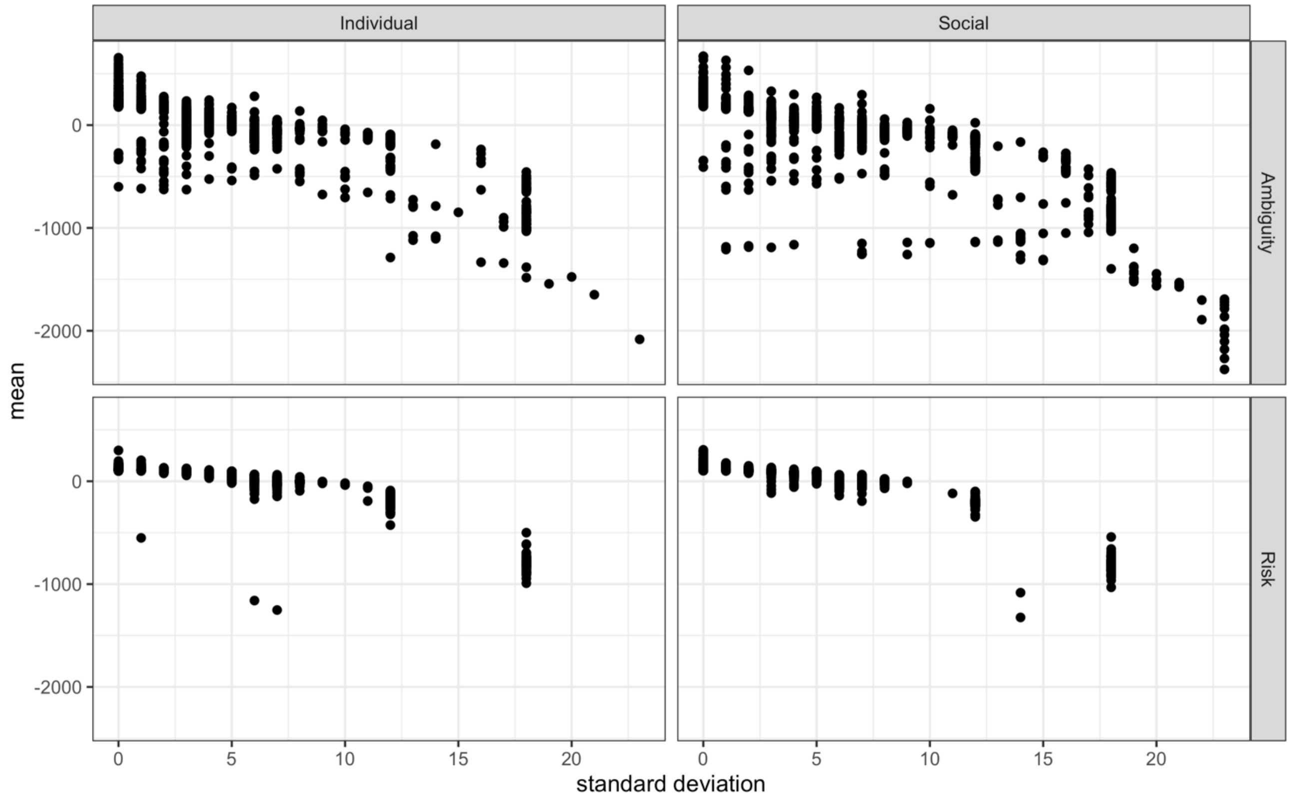
Each choice's expectation was measured separately for both ambiguity and risk conditions based on the choice history of participants by multiplying mentioned probabilities with the score that was earned in that round (Eq. 1). The other variable used here is variance which is calculated by Eq. 2. X_H is the high payoff for the selected option, and X_L is the low payoff.

$$Expectation_{it} = (scorew_{it} * probabilityW_{it}) + (scoreL_{it} * probabilityL_{it}) \quad (1)$$

$$Variance_{it} = probabilityW_{it} * (X_H - expectation_{it})^2 + probabilityL_{it} * (X_L - expectation_{it})^2 \quad (2)$$

Figure 1.4 shows the scatter plot of the expected value for each chosen option plotted against its standard deviation (square root of variance). As can be understood from this plot, the range of expectation and the standard deviation have the highest range in the social ambiguity condition and the lowest range for both risk conditions. A similar pattern was shown for both ambiguity and risk conditions. However, standard deviation has a higher range in social ambiguity conditions. Standard deviation is smaller in risk conditions as people know about the number of cards and avoid bad decisions. This shows that they make more rational decisions compared to people in the ambiguity group.

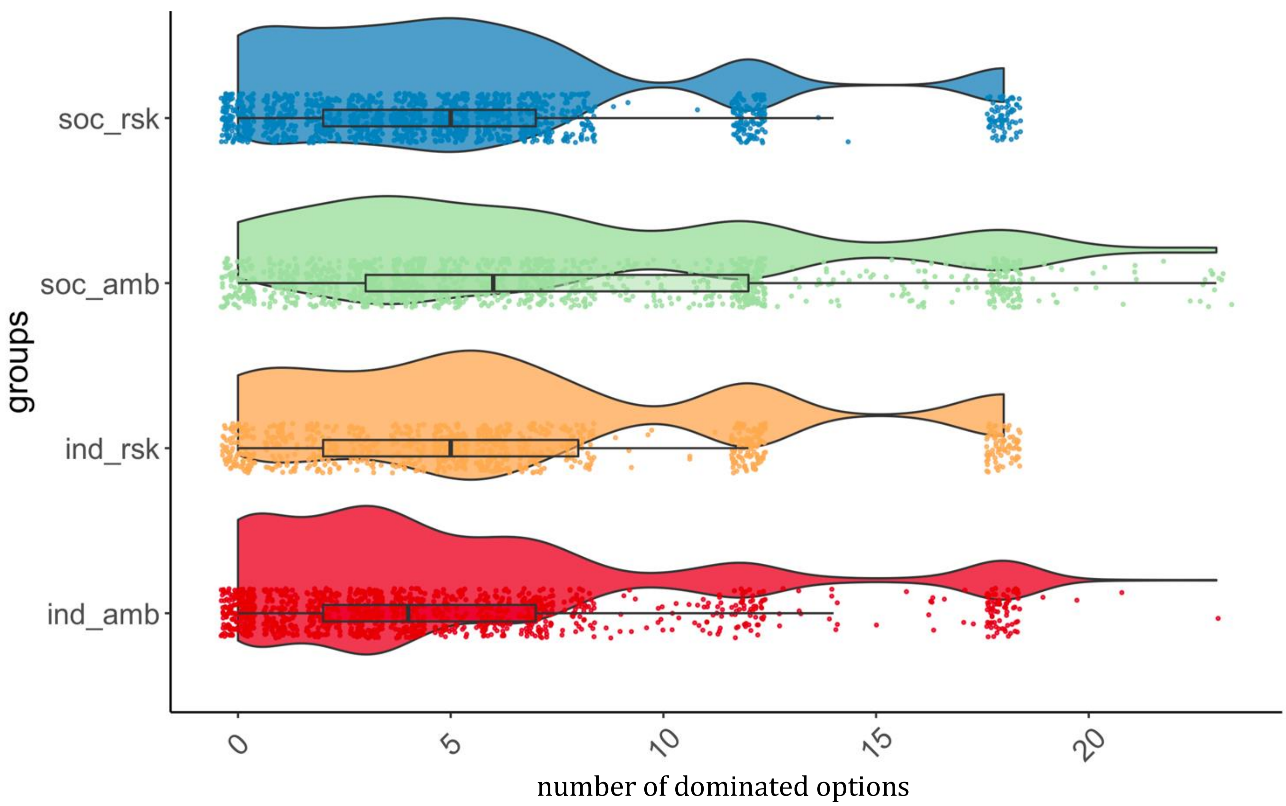
Figure 1.4: Scatter plot for the standard deviation and expectation of selected option for four conditions



These values for mean and variance were calculated for all possible options, not only for the chosen options. The number of options with a higher mean and lower variance than the selected option was measured for each participant in every trial to measure dominance. Thus, every participant had 50 values for this measurement, expressing her taken risk. The maximum number of dominances is 23, which means the worst option is selected, and all the other options were better than the selected one. The minimum is 0, which means that the selected option is the best compared to all the other possibilities.

Figure 1.5 depicts the entire distribution of the dominated options for each condition. As can be understood from this plot, the social ambiguity group has higher values for dominated options and is more expanded than the other groups. On the other hand, individual ambiguity is the group with the highest zero-dominated values. The median point of each group shows the highest value for social ambiguity and the lowest value for individual ambiguity, while social risk and individual risk have similar medians.

Figure 1.5: Number of dominated option distribution over conditions

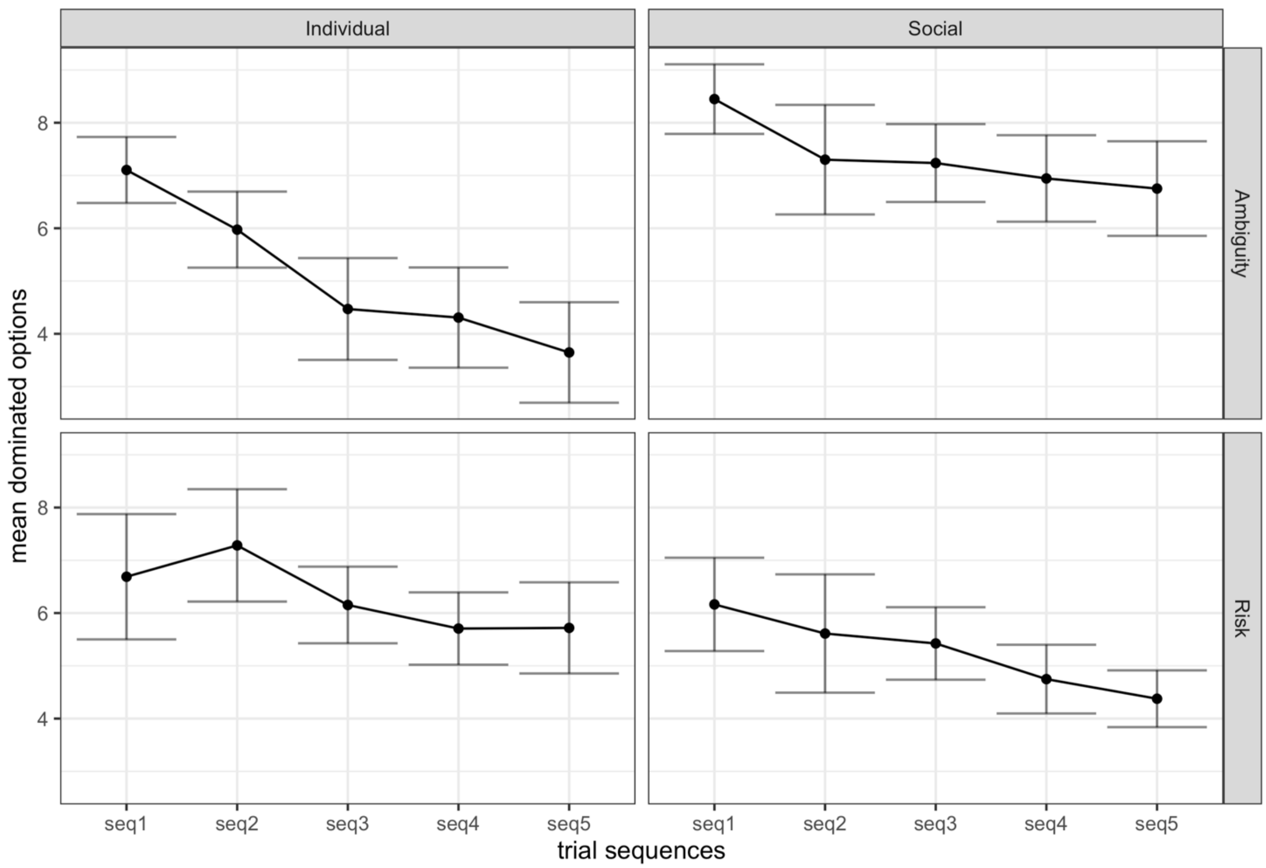


Distribution of the dominated options where the highest value for dominated option is *23*, and the lowest is *0*. Each value shows the total number of dominated options in each condition. *0* means the selected option is the dominance option, *1* means the selected option was dominated by one, and so on.

This depicts social ambiguity as a group with the highest risk-taking level, while individual ambiguity is the group with the lowest risk level. Individual risk and social risk are placed in between and behave similarly. It is noteworthy to add that social ambiguity had the lowest performance across conditions that significantly differed from other groups, and participants made less rational decisions in this group. Here performance is measured by the number of dominated options one did not choose; the higher this number, the worse the performance. Lower values are equivalent to higher performance, as participants chose safer options with higher expectations and lower variances rather than the other possible options.

Figure 1.6 shows that participants learn to choose better options regarding their dominance through time (each sequence consists of an average over ten time-points). Lines with negative slopes show a decrease in the number of dominated options in each choice. However, individual ambiguity has the most remarkable change with the highest negative slope. The distinction between the range of temporal changes in social ambiguity and individual ambiguity is high, but social risk and individual risk ranges are almost similar.

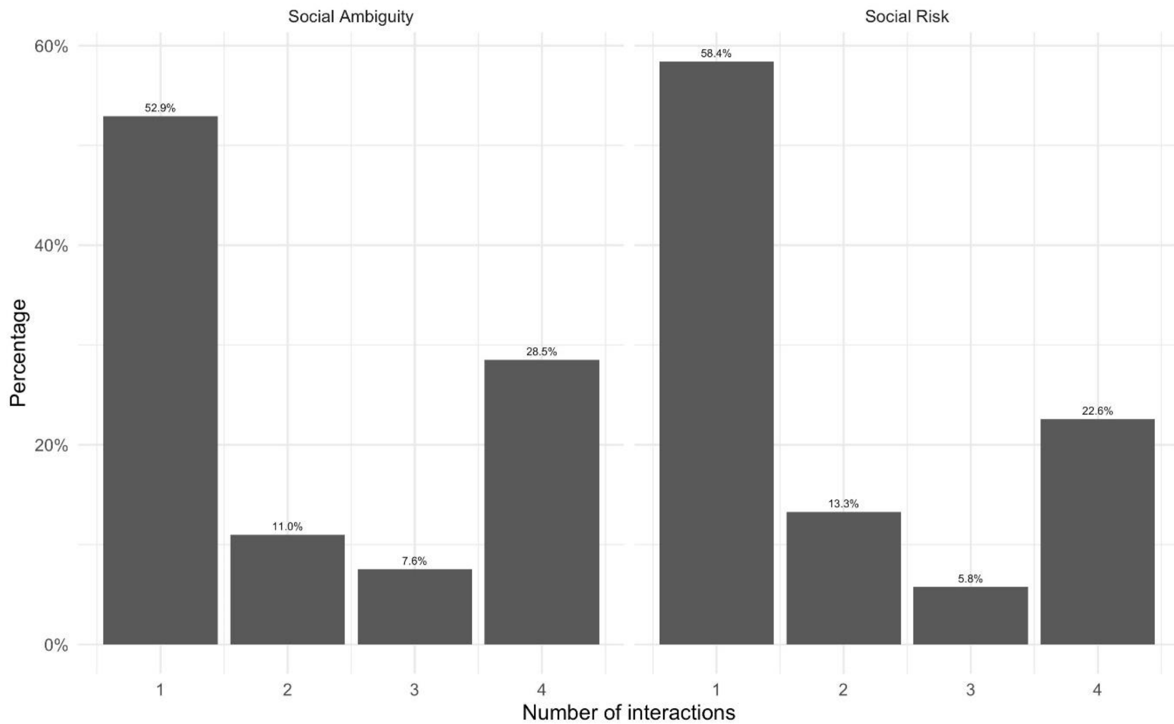
Figure 1.6: Participants' performance in each condition over sequences of 10 trials



1.3.2 Dependent variable: Interaction

As mentioned above, participants could see the results of others' decisions in the two social conditions. They were able to click on none, one, two, three, or all the other persons. This option is attractive as participants can see the exact color group chosen by the others if they clicked on them. This information could be helpful for them to find out the color of the computer card in each round. As it is shown in Figure 1.2, after a choice, participants can only see if their choice was wrong or right, but not the color of the computer card. Clicking on the others' emojis gives them this opportunity to find out what that was. We refer to the

Figure 1.7: Histogram of social interactions for both risky and ambiguous conditions while 1, 2, 3 and 4 are number of clicks.



number of clicks as a participant's interaction score. Overall, out of 5000 possible clicks, 517 clicks were made by participants, which suggests that the feature was not very appealing. Figure 1.7 shows histograms for the interaction score in the social risk and social ambiguity conditions to get a sense of the feature's heterogeneity. More than half of the clicks were on one person, and the next prominent one was for four clicks (more than 20%). Clicks on three other people was the lowest total value.

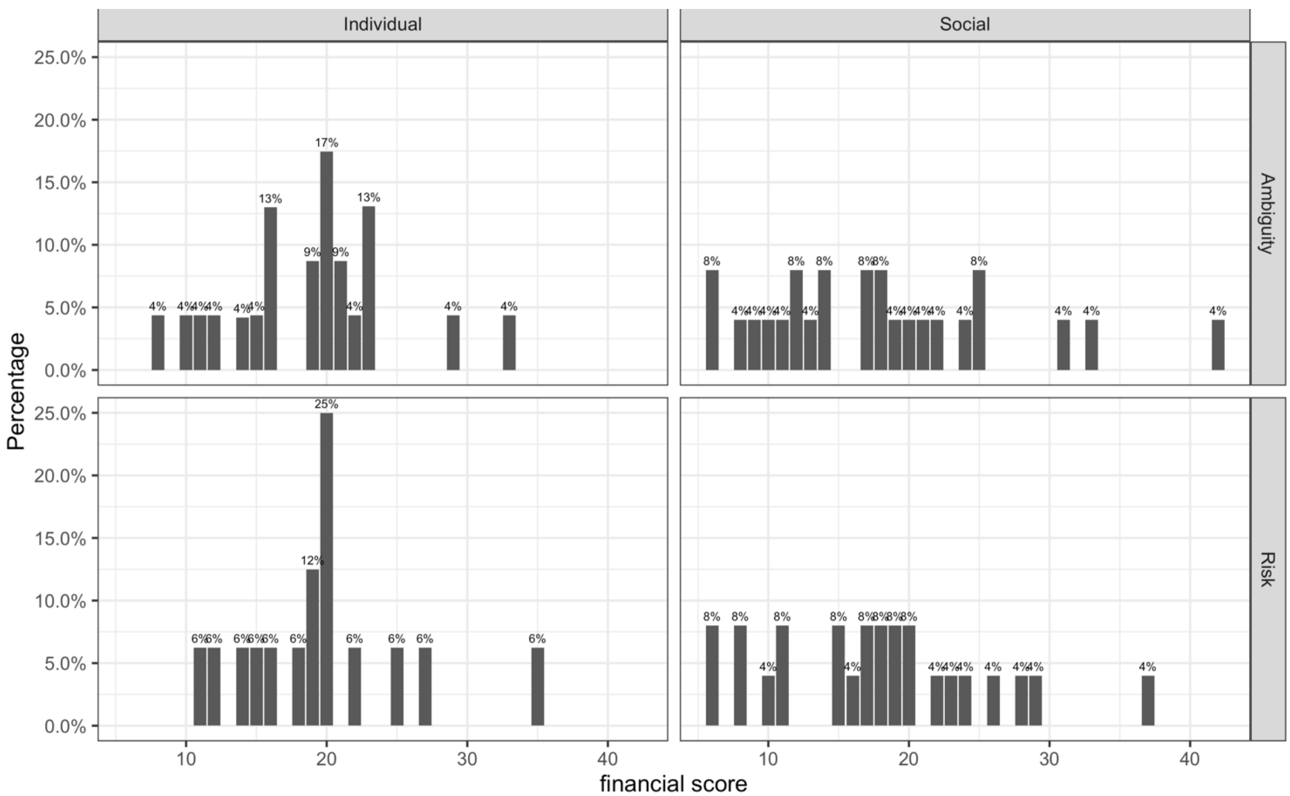
1.3.3 Self-reported risk taking

Figure 1.8 shows the histogram of the participants' taken score in the financial subscale of the DOSPERT questionnaire in each condition. The highest possible score is 50, and the lowest is 0. The average score in social ambiguity was 17.88 (SD= 8.6), social risk was 17.72 (SD= 7.5), individual ambiguity was 18.75 (SD=5.7), and individual risk was

19.6 (SD=5.7). Thus, 34% of the participants in the individual ambiguity scored higher than the average; it was 32% for social ambiguity, 28% for social risk, and 24% for individual risk.

Thus, a higher tendency of risk-taking showed in individual ambiguity as it had the highest coefficient. Social ambiguity, social risk and individual risk were placed in the other levels, respectively. The effect of this factor is controlled in the analysis.

Figure 1.8: Histogram of the participants financial score in each condition



1.3.4 Color preference

While a rational decision-maker would not respond to the specific color in the experiment, some literature shows an aversion to choosing red colors in risky decision-making tasks. For example, Gnambs et al. (2015), in a BART experiment with two colors of balloons, showed a more cautious behavior in a red condition versus blue [64].

On the other hand, in a recent study, Greiner (2020) [65] was unsuccessful in replicating previous exposure to red and blue colors on mood. Hence, he concluded that experimental economists do not need to worry about the potential confound of colors. Similar to him, Mao et al. (2018) [66] showed that there is no effect of color in risk-taking behavior.

Figure 1.9 shows the distribution of the preferred colors in this study. Overall, there is no significant difference in choosing specific colors except for purple, which was selected less than the other colors.

People in social and individual risk conditions preferred green slightly over the other colors. However, there is no evidence in the literature toward the effect of these colors on risk-taking, and the most prominent colors are red and blue. In order to test if red and blue are preferred or not, we investigate the percentage of choosing these colors in each group. This is done by counting the number of selected colors in each trial and dividing them into the total number of colors.

Figure 1.9: Distribution and median of the preferred color in each condition

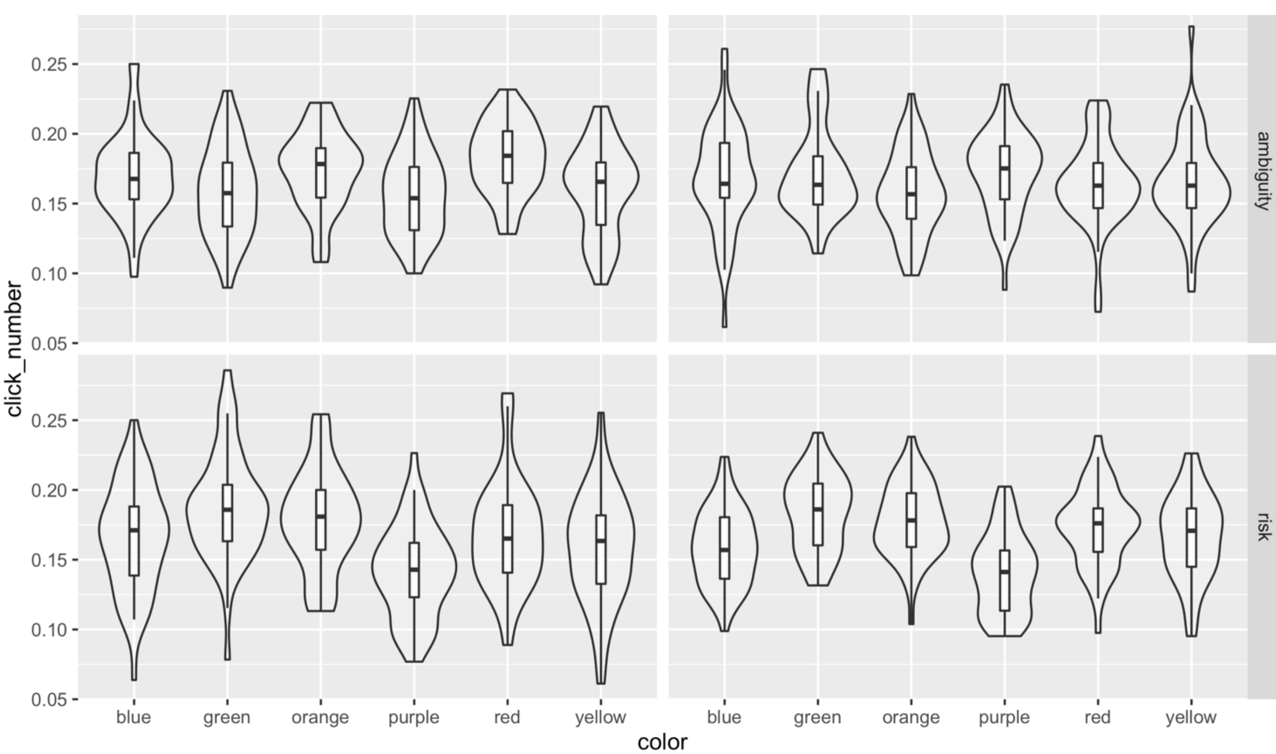
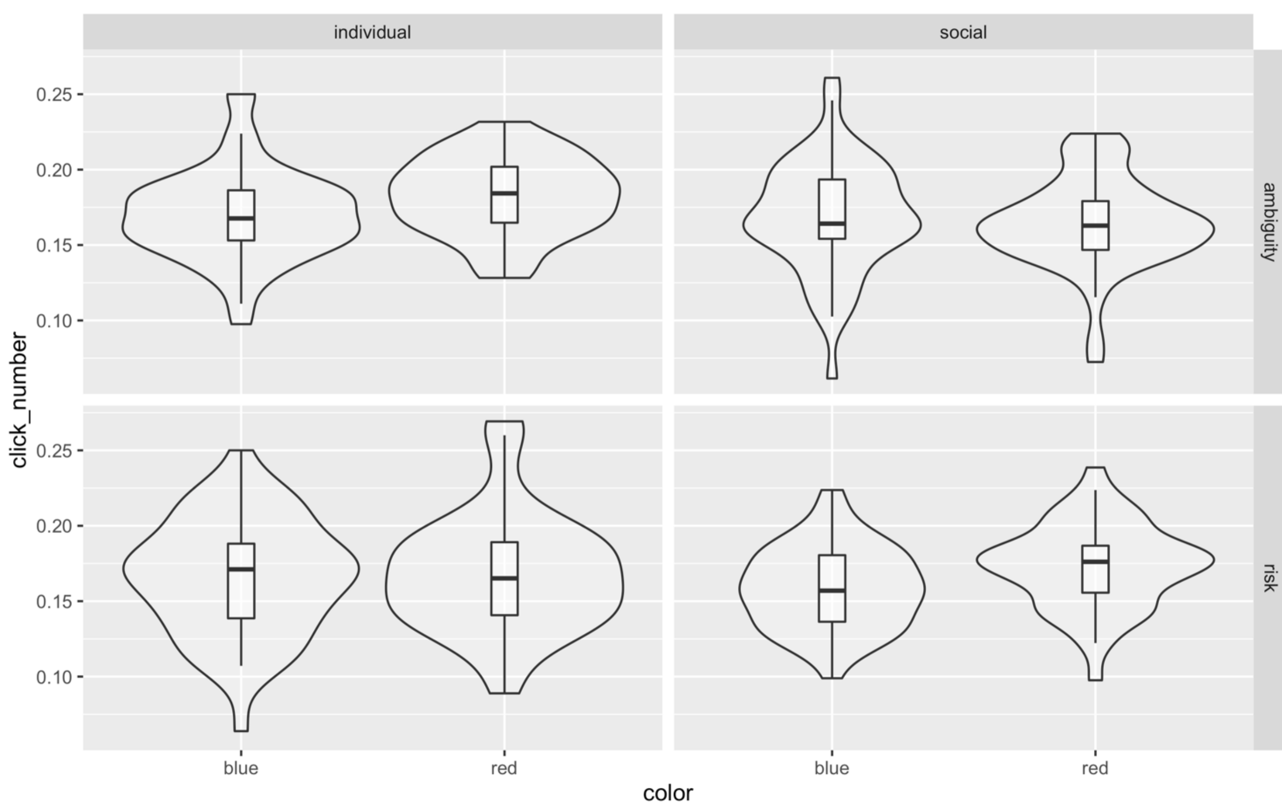


Figure 1.10 shows the distribution and the median number of blue and red colors chosen by the participants in all conditions. Overall blue and red did not differ significantly ($\chi2(2) = 1.6$, $p = .2$); however, there is a slight difference in social risk and individual ambiguity, where red color was selected more. Our finding is in contrary to the Gnambs et al. (2015) study [64], and thus a risky situation did not lead to not choosing the red color.
It is noteworthy to mention that all participants in all groups faced the same number of colors to choose from; thus, the effect of colors on risk-taking was already controlled using a similar experimental design.

Figure 1.10: Distribution and median of red and blue colors in each condition



1.3.5 Feedback

Feedback was given to the participants, as was shown in Figure 1.2. It provided them with information about their guess. If their guess was true, they received a message that they won some score related to their choice; otherwise, they received their loss with a message about their negative score. Feedback could be one of the values ±1200, ±600, ±400, ±300. As Vuculescu and Schuermann suggested, positive feedback can intensify risk aversion, and negative feedback has the opposite effect [55–57]. The effect of this factor is controlled in the analysis.

1.4 Results

Because the data is collected repeatedly for each person and is not normally distributed, it is not possible to use common inferential models like ANOVA or t-test. Thus, a linear mixed model was used. To capture dependency in repeated measures and nonlinearity in data, the lme4 package [67,68] in R was used for the analysis. The dominated number of options or interactions was included as the dependent variable for testing each hypothesis. The related fixed effect of condition groups was placed as an independent factor. Feedback and financial risk-taking score were used as control variables. Gender was removed from the analysis as it did not show any effect on the related outcome. Participants' repeated actions were defined as a random effect using their ID. The Likelihood ratio test was used to examine the significance of the independent variables on the dependent variable. It is done by comparing two models, one with the factor under investigation, and the other without that factor.

1.4.1 Test of Hypothesis 1: Participants in individual risk condition take more risks than in individual ambiguity

This hypothesis was tested using the number of dominated options as the dependent variable and an independent dummy variable has used as group name (individual ambiguity vs. individual risk) as factors of a linear mixed model. Because this task was repeated t times for each person i, residual variation of individuals and task's repetition were controlled using the error term (ε_{it}) in a random effect.

It solved non-independence by considering a different baseline value for each subject [69]. Eq. 3 shows the definition of this model.

$$number\ of\ dominated\ options_{it} = \alpha_{Individual\ Ambiguity/Individual\ Risk} + \beta_{feedback_{i(t-1)}} + \gamma financial\ score_i + \varepsilon_{it}$$

(3)

Table 1.2 shows the coefficient of the model. τ showed variance for the random effect, and σ^2 depicted this value for the residuals. The random effect controls the repetition of each trial, and residuals were factors that could not be explained by the model using our data. Intraclass Correlation Coefficient (ICC) was used to give a sense of how much variance was explained by the random effect, and it was included in 23% of the variance. The other factors explain the remaining variances in the model. This model stated a significant effect of individual risk or individual ambiguity in choosing high-risk options, as participants in individual risk took more risk (mean = 6.32 ± 5.1) than in individual ambiguity (mean = 5.1 ± 4.9).

Feedback also positively affected the number of dominated options and increased risk-taking by the factor of 5.1 - 0.6. The Likelihood ratio test was used to examine the independent variable's effect (being in one of the individual groups) on the dependent ones (dominated options). It did not show a significant difference between this model and the null model, which is the model without the group's effect ($\chi2(1) = 2.4$, $p = .12$) and could not prove the first hypothesis.

Table 1.2: Model coefficients for chosen option risk in individual risk vs. individual ambiguity.

	Number of dominated options	
Predictors	Estimates	p
(Intercept)	5.11 (0.76)***	<0.001
group name [individual Risk]	1.25 (0.8)	0.1
feedback	-0.6(0.1) ***	<0.001
financial	-0.17(0.45)	0.66

Random Effects	
σ^2	18.53
$\tau_{00\ id}$	5.52
ICC	0.23
N id	39

$*p < .05$. $**p < .01$. $***\ p < .001$. (*Std. Error*)

1.4.2 Test of Hypothesis 2.1: There is no difference between social risk and individual risk groups in their risk-taking

The linear mixed model was used to test hypothesis 2.1, similar to the previous part. However, instead of having individual risk and individual ambiguity as group labels, being in social risk or individual risk groups was tested here. Other factors remained the same. Eq. 4 shows this model.

$$number\ of\ dominated\ options_{it} = \alpha_{Individual\ Risk/Social\ Risk} + \beta_{feedback_{i(t-1)}} + \gamma financial\ score_i + \varepsilon_{it} \tag{4}$$

Results did not show any significant effect in conditions, and there was no relation between the group effects on dominance (Table 1.3). Similarly, the likelihood ratio tests did not show a significant difference between the model and its related null model ($\chi2(1) = 1.6$, $p = .2$). So, there was no effect of being in social risk or individual risk group on risk-taking, and the mentioned hypothesis was accepted.

Table 1.3: Model coefficients for chosen option risk in individual risk vs. social risk.

	Number of dominated options	
Predictors	Estimates	p
(Intercept)	6.29 (0.6)***	<0.001
group name [Social Risk]	-0.98 (0.77)	0.2
feedback	-0.34(0.09) ***	<0.001
financial	0.35(0.37)	0.35
Random Effects		
σ^2	16.57	
$\tau_{00\ id}$	5.34	
ICC	0.24	
N id	41	

$*p < .05$. $**p < .01$. $***\ p < .001$. (*Std. Error*)

1.4.3 Test of Hypothesis 2.2: People in individual ambiguity condition take lower risks than in social ambiguity

We used the linear mixed model to test hypothesis 2.2. However, instead of individual risk and individual ambiguity as group labels, the effect of being in social ambiguity and individual ambiguity was tested here. Other factors remained fixed. Eq. 5 shows this model.

$$number\ of\ dominated\ options_{it} = \alpha_{Individual\ Ambiguity/Social\ Ambiguity} + \beta_{feedback_{i(t-1)}} + \gamma financial\ score_i + \varepsilon_{it}$$

(5)

Table 1.4 shows the results for testing this hypothesis. It shows a higher number of dominated options in social ambiguity (mean = 7.34 ± 5.65) than individual ambiguity (mean = 5.1 ± 4.92) with the consistent feedback effect. At the same time, other factors do not have any significant effect on the model's outcome. There is a significant difference in comparing the number of dominated options in social ambiguity than individual ambiguity using the likelihood ratio test ($\chi2(1) = 6.67$, $p = .009$). This result confirmed the mentioned hypothesis.

Table 1.4: Model coefficients for chosen option risk in individual ambiguity vs. social ambiguity.

	Number of dominated options	
Predictors	Estimates	p
(Intercept)	5.16 (0.57)***	<0.001
group name [Social ambiguity]	2.12 (0.8)**	0.007
feedback	-0.35(0.1) ***	<0.001
financial	-0.13(0.4)	0.75
Random Effects		
σ^2	20.57	
$\tau_{00\ id}$	7.09	
ICC	0.26	
N_{id}	48	

$*p < .05$. $**p < .01$. $***\ p < .001$. (*Std. Error*)

1.4.4 Test of Hypothesis 3: Participants make more interactions in the social ambiguity condition than in the social risk

The last hypothesis had more interaction in social ambiguity than in the social risk group. Similar to the other models (Eq. 3, Eq. 4 and Eq. 5), a linear mixed model was used (Eq. 6). The interaction was measured as the dependent variable by the number of clicks people made on others. Group labels with social risk and social ambiguity were expressed as the independent variables, and other variables were similar to the variables in the other models.

$$number\ of\ click_{it} = \alpha_{Social\ ambiguity/Social\ Risk} + \beta_{feedback_{i(t-1)}} + \gamma financial\ score_i + \varepsilon_{it} \quad (6)$$

Table 1.5 shows the results of testing hypothesis 3. Results showed that participants did not click differently based on the group they belonged to ($\chi2(1) = 0.003$, $p = .95$), and also feedback was not an effective factor regarding the number of clicks. However, having a higher financial score from the questionnaire significantly increased the number of clicks ($\chi2(1) = 4.7$, $p = .03$).

Table 1.5: Model coefficients for interaction in social risk vs. social ambiguity.

	Number of clicks	
Predictors	Estimates	p
(Intercept)	1.69 (0.19)***	<0.001
group name [Social Risk]	0.02 (0.28)	0.95
feedback	-0.02(0.03)	0.47
financial	0.31(0.14)*	0.03
Random Effects		
σ^2	0.5	
$\tau_{00\ id}$	0.69	
ICC	0.58	
N_{id}	42	

$*p < .05$. $**p < .01$. $***\ p < .001$. (*Std. Error*)

1.4.5 Exploratory analysis: Competition

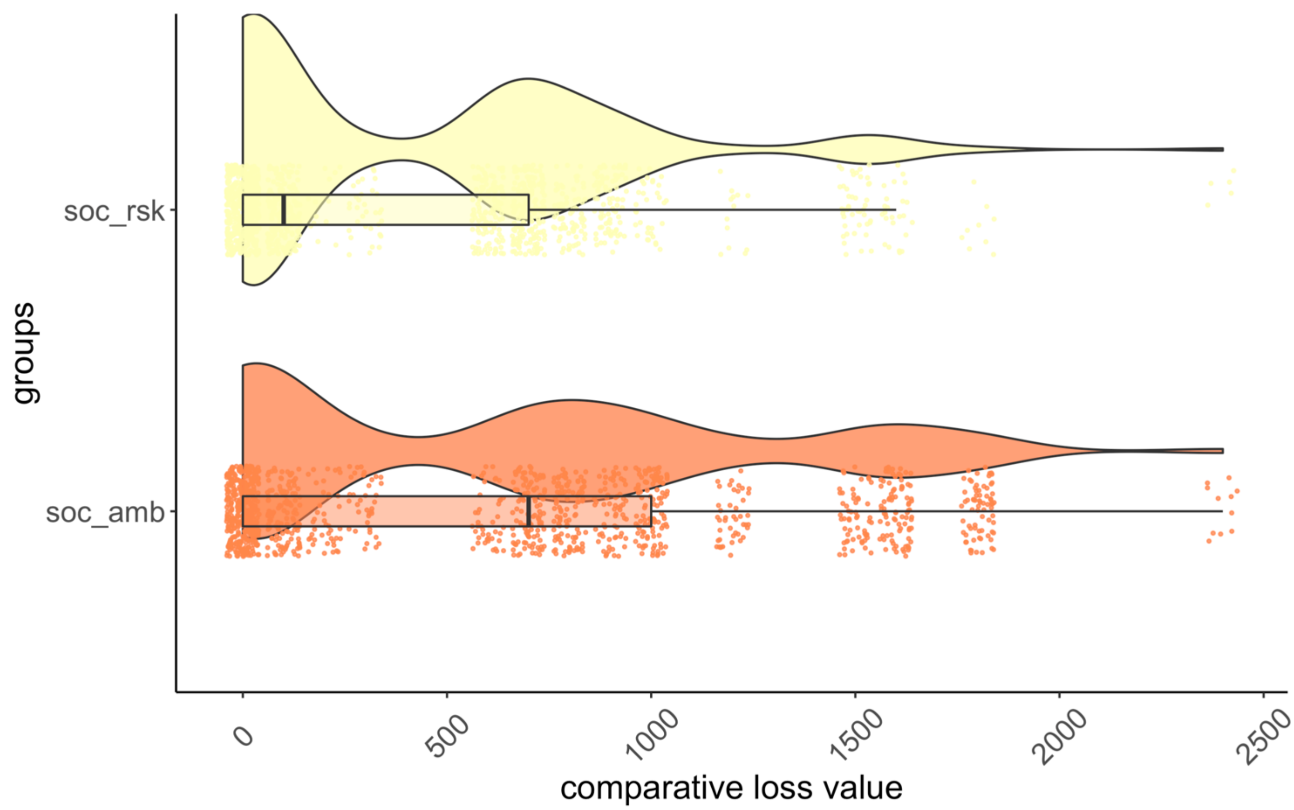
According to the findings of this study, participants took more risks in social ambiguity. Here we are looking for a reason behind this behavior as there was no significant evidence in social interactions. Participants' advantage in the social conditions is to see each other's outcome in every round before making any clicks (Figure 1.3). We designed the experiment such that participants get encouraged to click to see others' outcome for further information. However, the results show that this strategy was not successful. As Mishra, Barclay, and Lalumière (2014) [2] showed, such information affects risk-taking behavior competitively. They exposed participants to a competitive (dis)advantage IQ test followed by an economic decision-making task and saw a disadvantage, elevating risk-taking behavior [2]. Getting the idea from their study, competition is another factor that could influence a participant's decisions, and here it was investigated exploratorily.

The difference between one's taken score with the maximum taken scores of other participants in a previous round was counted as a competitive factor. If the difference was positive (her guess was true), she gained more than the whole group (gain domain-advantageous). Thus, there is no motive for taking higher risks to make up for a relative shortfall. However, if the difference was negative (loss domain-disadvantageous), others achieved a higher score than her. Hence, she might try to compensate by taking higher risks in the next round. Here, regarding the mentioned study on the effect of disadvantageous on risk-taking, the loss domain was used. Eq. 7 was used to capture this value. The comparative loss will be zero when others gain less. On the other hand, when one participant gains lower than others, the comparative loss will be the difference between their scores.

$$\text{comparative loss} = \max(\text{max other score} - \text{own score}, 0) \tag{7}$$

This measure was used to test the effect of being in one of the social conditions. Figure 1.11 shows the distribution of this factor in both social risk and ambiguity. Social ambiguity has a higher distribution and median than the social risk in this factor, meaning that people in social ambiguity had lower outcomes than others.

Figure 1.11: Distribution of comparative loss value over social conditions



Distribution of the comparative loss where the highest value for it is *2500*, and the lowest is *0*. Each value shows the comparative score in a loss domain

The model in Eq. 8 was applied to social risk and social ambiguity together with financial and gender factors. Feedback was removed because it was already considered in the calculation of comparative loss. As Table 1.6 shows, being in social ambiguity or risk groups significantly affects the comparative loss. It is higher in social ambiguity and lower in social risk ($\chi 2(1) = 13.66$, $p = .0002$). This means that participants had lower scores than others in social ambiguity, while they had higher scores than others in social risk. Having this result guided us to test the effect of the comparative loss factor on dominated options. As Table 1.7 shows, it increased the number of dominated options, and with the likelihood ratio test, this effect is statistically significant ($\chi 2(1) = 8.23$, $p = .004$).

$$comparative\ loss_{it} = \alpha_{Social\ ambiguity/Social\ Risk} + \gamma financial\ score_i + \varepsilon_{it} \qquad (8)$$

Table 1.6: Effect of being in social ambiguity and social risk on comparative loss

	Comparative loss	
Predictors	Estimates	p
(Intercept)	0.19 (0.07)**	0.005
group name [Social Risk]	-0.37(0.09)***	<0.001
financial	0.06(0.05)	0.2
Random Effects		
σ^2	0.87	
$\tau_{00\ id}$	0.09	
ICC	0.1	
N_{id}	50	

$*p < .05$. $**p < .01$. $***\ p < .001$. (*Std. Error*)

Table 1.7: Model coefficients for chosen option risk in social ambiguity vs. social risk with the factor of comparative loss

	Number of dominated options	
Predictors	Estimates	p
(Intercept)	7.28 (0.53)***	<0.001
group name [Social Risk]	-1.97(0.76)**	0.009
Comparative loss	0.27(0.09)**	0.004
financial	0.23(0.4)	0.55
Random Effects		
σ^2	18.74	

$\tau_{00\ id}$	6.78
ICC	0.27
N id	50

$*p < .05. **p < .01. *** p < .001.$ (*Std. Error*)

1.5 Conclusion

In this study, the contribution of two factors, risk and ambiguity, in decision-making and in the decision-maker's circumstances, whether individually or with access to others' information, was examined.

It was shown that contrary to our hypothesis, people in individual conditions behave similarly with no trace of ambiguity aversion.

On the other hand, as we expected, being in social risk or individual risk conditions makes people use their objective utility function to measure expectation and thus resulted in similar behavior.

Hence, ambiguity condition leads people to use subjective expected utility. It resulted in a different behavioral pattern in the two conditions of social ambiguity and individual ambiguity and confirmed our hypothesis. Thus, it seems that social situations can increase risk-taking by manipulating the subjective expected utility function.

Testing the effect of social ambiguity or social risk on the tendency to earn more information in social ambiguity was rejected. Both groups were mainly unwilling to click on others.

Based on what Ellsberg [12] suggested, uncertainty had a more significant impact on people's behavior. He explained that decision-makers' preferences on uncertain situations could be defined by the outcome and the belief about that outcome. The belief in the risky situation is objective and, in the ambiguous situation, is subjective. It means that people consider existing known probabilities for options' outcomes in risk situations while they use their subjective probabilities in ambiguity; thus, their responses are different toward these conditions [22–24]. This explains the observed behavior in this study, considering that people's evaluation in both risk conditions was based on objective expected utility known in both conditions. Thus, they behaved similarly and tried to take less risk. However, on the other hand, decisions are made by a subjective expected utility in the ambiguity condition, and people prefer to choose an option with a higher subjective expected utility rating than a lower one [37].

It means that participants' subjective expected utility in social ambiguity conditions might be higher than in individual ambiguity. Based on Yechiam et al. (2008) [37], a shift in risk-taking appears when people have been exposed to other risky behaviors, which can be explained by changing subjective expected utilities in social situations. However, we did not collect this subjective information from participants during the experiment. This information can show participants' confidence about selected options [70], which is suggested to be collected in future studies to test the relation between subjective expected utility and participants' selected options in social situations.

On the other hand, while interaction rate did not significantly affect conditions, comparative loss showed a significant effect on increasing risk-taking in social ambiguity. Thus, people in social ambiguity that face a higher amount of comparative loss behave more compensatory by participating in more risky choices.

Risk-taking has a close relation to performance in a competitive context [2,69]. Gärling et al. (2020) [69] observed an increase in risk-taking when participants are motivated to compete, while Mishra, Barclay, and Lalumière (2014) [2] showed that risk-taking is increased when confronted with cues of competitive disadvantage. It is more probable for people to engage in criminal or aggressive behaviors if they failed in economic competition.

Consequently, people's behavior in social ambiguity condition describes a comparison between each person's outcome with the highest outcome from others and trying to compensate by behaving similar to them. It was shown that the ambiguity group was more prone to be influenced by others because of using subjective utility function and also higher comparative loss compared with risky ones.

The strength of the present study was the design of an integrated test to assess risk in the different levels of risk vs. ambiguity and social vs. individual conditions and the possibility to measure interactions accounting for information collected from the environment. However, the low number of rounds for running the task is the weakness of this study. Having lower number of rounds than the number of cards when they were taken without replacement made the calculation of probabilities challenging. However, the method provided here to calculate the probabilities was able to solve this problem to some extent.

It would be beneficial if future studies try to investigate where people actually use information in social condition. Here, it is not clear if participants really looked at the options and used the information they had access to or not. Eye-tracking is a helpful tool to find the exact position of where people look. Using this tool, data could be compared between social risk and social ambiguity to find out which group look for more information provided by others. Based on uncertainty reduction theory and the outcome of this study, it is expected that ambiguity will have the highest rate.

The last consideration is about the contradiction from ambiguity aversion theory. The current study results show that in the presence of others' information, participants in the group presented with ambiguous options do not show any preferences for choosing safer compared with the ones presented with the risky options. The conclusion is that ambiguity aversion has only occurred in the situation of the comparison with higher or lower information about the outcomes on an individual level. This results confirmed findings of Kocher et al. (2015) [28] that ambiguity aversion is sensitive to the context and domain of the decision-making task; thus it should be considered carefully. Otherwise, the prediction of ambiguity aversion theory is not generalizable.

References

1. Yates, J. (1992). *Risk-taking behavior.* John Wiley & Sons.

2. Mishra, S., Barclay, P., & Lalumière, M. L. (2014). Competitive disadvantage facilitates risk taking. *Evolution and Human Behavior*, *35*(2), 126–132.

3. Euteneuer, F., Schaefer, F., Stuermer, R., Boucsein, W., Timmermann, L., Barbe, M. T., Ebersbach, G., Otto, J., Kessler, J., & Kalbe, E. (2009). Dissociation of decision-making under ambiguity and decision-making under risk in patients with Parkinson's

disease: A neuropsychological and psychophysiological study. *Neuropsychologia*, *47*(13), 2882–2890.

4. Fujino, J., Hirose, K., Tei, S., Kawada, R., Tsurumi, K., Matsukawa, N., Miyata, J., Sugihara, G., Yoshihara, Y., & Ideno, T. (2016). Ambiguity aversion in schizophrenia: An fMRI study of decision-making under risk and ambiguity. *Schizophrenia Research*, *178*(1–3), 94–101.
5. Isen, A. M. (2001). An influence of positive affect on decision making in complex situations: Theoretical issues with practical implications. *Journal of Consumer Psychology*, *11*(2), 75–85.
6. Maes, J. H., Woyke, I. C., & Brazil, I. A. (2018). Psychopathy-related traits and decision-making under risk and ambiguity: An exploratory study. *Personality and Individual Differences*, *122*, 190–194.
7. Bechara, A., Damasio, H., Tranel, D., & Damasio, A. R. (2005). The Iowa Gambling Task and the somatic marker hypothesis: Some questions and answers. *Trends in Cognitive Sciences*, *9*(4), 159–162.
8. Camerer, C. F., Bhatt, M., & Hsu, M. (2007). *Neuroeconomics: Illustrated by the study of ambiguity aversion*. Citeseer.
9. Deisenhammer, E. A., Schmid, S. K., Kemmler, G., Moser, B., & Delazer, M. (2018). Decision making under risk and under ambiguity in depressed suicide attempters, depressed non-attempters and healthy controls. *Journal of Affective Disorders*, *226*, 261–266.
10. Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, 643–669.

11. FeldmanHall, O., Glimcher, P., Baker, A. L., & Phelps, E. A. (2016). Emotion and decision-making under uncertainty: Physiological arousal predicts increased gambling during ambiguity but not risk. *Journal of Experimental Psychology: General*, *145*(10), 1255.

12. Knight Frank, H. (1921). Risk, uncertainty and profit. *Книга*.

13. Fox, C. R., & Tversky, A. (1995). Ambiguity aversion and comparative ignorance. *The Quarterly Journal of Economics*, *110*(3), 585–603.

14. Etner, J., Jeleva, M., & Tallon, J.-M. (2012). Decision theory under ambiguity. *Journal of Economic Surveys*, *26*(2), 234–270.

15. Johnson, J. G., & Busemeyer, J. R. (2010). Decision making under risk and uncertainty. *Wiley Interdisciplinary Reviews: Cognitive Science*, *1*(5), 736–749.

16. Camerer, C., & Weber, M. (1992). Recent developments in modeling preferences: Uncertainty and ambiguity. *Journal of Risk and Uncertainty*, *5*(4), 325–370.

17. Trautmann, S. T., Vieider, F. M., & Wakker, P. P. (2008). Causes of ambiguity aversion: Known versus unknown preferences. *Journal of Risk and Uncertainty*, *36*(3), 225–243.

18. Howard, J. (2019). Ambiguity Effect. In *Cognitive Errors and Diagnostic Mistakes* (pp. 15–19). Springer.

19. Kramer, M. W. (1999). Motivation to reduce uncertainty: A reconceptualization of uncertainty reduction theory. *Management Communication Quarterly*, *13*(2), 305–316.

20. Santos, L. R., & Rosati, A. G. (2015). The evolutionary roots of human decision making. *Annual Review of Psychology*, *66*, 321–347.

21. Martinez-Correa, J. (2012). *Decision under Risk, Uncertainty and Ambiguity: Theory and Experiments*. Georgia State University.

22. Halevy, Y. (2007). Ellsberg revisited: An experimental study. *Econometrica*, *75*(2), 503–536.

23. Machina, M. J., & Siniscalchi, M. (2014). Ambiguity and ambiguity aversion. In *Handbook of the Economics of Risk and Uncertainty* (Vol. 1, pp. 729–807). Elsevier.

24. Segal, U. (1987). The Ellsberg paradox and risk aversion: An anticipated utility approach. *International Economic Review*, 175–202.

25. Kahn, B. E., & Sarin, R. K. (1988). Modeling ambiguity in decisions under uncertainty. *Journal of Consumer Research*, *15*(2), 265–272.

26. Machina, M. J. (2009). Risk, ambiguity, and the rank-dependence axioms. *American Economic Review*, *99*(1), 385–392.

27. Snow, A. (2010). Ambiguity and the value of information. *Journal of Risk and Uncertainty*, *40*(2), 133–145.

28. Kocher, M. G., Lahno, A. M., & Trautmann, S. (2015). *Ambiguity aversion is the exception*.

29. Chow, C. C., & Sarin, R. K. (2001). Comparative ignorance and the Ellsberg paradox. *Journal of Risk and Uncertainty*, *22*(2), 129–139.

30. Nocetti, D. C. (2018). Ambiguity and the value of information revisited. *The Geneva Risk and Insurance Review*, *43*(1), 25–38.

31. Wittek, P., Liu, Y.-H., Darányi, S., Gedeon, T., & Lim, I. S. (2016). Risk and ambiguity in information seeking: Eye gaze patterns reveal contextual behavior in dealing with uncertainty. *Frontiers in Psychology*, *7*, 1790.

32. Bougheas, S., Nieboer, J., & Sefton, M. (2013). Risk-taking in social settings: Group and peer effects. *Journal of Economic Behavior & Organization*, *92*, 273–283.

33. Cross, R., Rice, R. E., & Parker, A. (2001). Information seeking in social context: Structural influences and receipt of information benefits. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, *31*(4), 438–448.

34. Qi, S., Footer, O., Camerer, C. F., & Mobbs, D. (2018). A collaborator's reputation can bias decisions and anxiety under uncertainty. *Journal of Neuroscience*, *38*(9), 2262–2269.

35. Clark, R. D., & Willems, E. P. (1969). Where is the risky shift? Dependence on instructions. *Journal of Personality and Social Psychology*, *13*(3), 215.

36. Masclet, D., Colombier, N., Denant-Boemont, L., & Loheac, Y. (2009). Group and individual risk preferences: A lottery-choice experiment with self-employed and salaried workers. *Journal of Economic Behavior & Organization*, *70*(3), 470–484.

37. Yechiam, E., Druyan, M., & Ert, E. (2008). Observing others' behavior and risk taking in decisions from experience. *Judgment and Decision Making*, *3*(7), 493.

38. Brunette, M., Cabantous, L., & Couture, S. (2015). Are individuals more risk and ambiguity averse in a group environment or alone? Results from an experimental study. *Theory and Decision*, *78*(3), 357–376.

39. Suzuki, S., Jensen, E. L., Bossaerts, P., & O'Doherty, J. P. (2016). Behavioral contagion during learning about another agent's risk-preferences acts on the neural representation of decision-risk. *Proceedings of the National Academy of Sciences*, *113*(14), 3755–3760.

40. Tomova, L., & Pessoa, L. (2018). Information about peer choices shapes human risky decision-making. *Scientific Reports*, *8*(1), 1–9.

41. Mobius, M., & Rosenblat, T. (2014). Social learning in economics. *Annu. Rev. Econ.*, *6*(1), 827–847.

42. Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, *357*(4), 370–379.

43. Gantner, A., & Kerschbamer, R. (2018). Social interaction effects: The impact of distributional preferences on risky choices. *Journal of Risk and Uncertainty*, *56*(2), 141–164.

44. Rosenquist, J. N., Murabito, J., Fowler, J. H., & Christakis, N. A. (2010). The spread of alcohol consumption behavior in a large social network. *Annals of Internal Medicine*, *152*(7), 426–433.

45. Stadtfeld, C., Vörös, A., Elmer, T., Boda, Z., & Raabe, I. J. (2019). Integration in emerging social networks explains academic failure and success. *Proceedings of the National Academy of Sciences*, *116*(3), 792–797.

46. Scherer, C. W., & Cho, H. (2003). A social network contagion theory of risk perception. *Risk Analysis: An International Journal*, *23*(2), 261–267.

47. Blais, A.-R., & Weber, E. U. (2006). A domain-specific risk-taking (DOSPERT) scale for adult populations. *Judgment and Decision Making*, *1*(1).

48. Charness, G., Karni, E., & Levin, D. (2007). Individual and group decision making under risk: An experimental study of Bayesian updating and violations of first-order stochastic dominance. *Journal of Risk and Uncertainty*, *35*(2), 129–148.

49. Li, S. (2003). The role of expected value illustrated in decision-making under risk: Single-play vs multiple-play. *Journal of Risk Research*, *6*(2), 113–124.

50. Boyer, T. W. (2006). The development of risk-taking: A multi-perspective review. *Developmental Review*, *26*(3), 291–345.

51. Duangpatra, K. N., Bradley, G. L., & Glendon, A. I. (2009). Variables affecting emerging adults' self-reported risk and reckless behaviors. *Journal of Applied Developmental Psychology*, *30*(3), 298–309.

52. Figner, B., & Weber, E. U. (2011). Who takes risks when and why? Determinants of risk taking. *Current Directions in Psychological Science*, *20*(4), 211–216.

53. Killgore, W. D., Grugle, N. L., Killgore, D. B., & Balkin, T. J. (2010). Sex differences in self-reported risk-taking propensity on the evaluation of risks scale. *Psychological Reports*, *106*(3), 693–700.

54. Lauriola, M., Panno, A., Levin, I. P., & Lejuez, C. W. (2014). Individual differences in risky decision making: A meta-analysis of sensation seeking and impulsivity with the balloon analogue risk task. *Journal of Behavioral Decision Making*, *27*(1), 20–36.

55. Billinger, S., Srikanth, K., Stieglitz, N., & Schumacher, T. R. (2021). Exploration and exploitation in complex search tasks: How feedback influences whether and where human agents search. *Strategic Management Journal*, *42*(2), 361–385.

56. Schuermann, B., Endrass, T., & Kathmann, N. (2012). Neural correlates of feedback processing in decision-making under risk. *Frontiers in Human Neuroscience*, *6*, 204.

57. Vuculescu, O. (2017). Searching far away from the lamp-post: An agent-based model. *Strategic Organization*, *15*(2), 242–263.

58. Eliashberg, J., & Winkler, R. L. (1978). The role of attitude toward risk in strictly competitive decision-making situations. *Management Science*, *24*(12), 1231–1241.

59. Eisdorfer, A., & Giaccotto, C. (2016). The St. Petersburg paradox and capital asset pricing. *Annals of Finance*, *12*(1), 1–16.

60. Sennetti, J. T. (1976). On Bernoulli, Sharpe, financial risk and the St. Petersburg paradox. *The Journal of Finance*, *31*(3), 960–962.

61. Libby, R., & Fishburn, P. C. (1977). Behavioral models of risk taking in business decisions: A survey and evaluation. *Journal of Accounting Research*, 272–292.

62. d'Acremont, M., & Bossaerts, P. (2008). Neurobiological studies of risk assessment: A comparison of expected utility and mean-variance approaches. *Cognitive, Affective, & Behavioral Neuroscience*, *8*(4), 363–374.

63. Koch, A. K. (2006). Lectures 3 and 4 Mean Variance Analysis'. *Royal Holloway, University of London*.

64. Gnambs, T., Appel, M., & Oeberst, A. (2015). Red color and risk-taking behavior in online environments. *PLoS One*, *10*(7), e0134033.

65. Greiner, B., & Stephanides, M. (2020). *The economics of color: A null result*.

66. Mao, T., Yang, J., Ru, T., Chen, Q., Shi, H., Zhou, J., & Zhou, G. (2018). Does red light induce people to be riskier? Exploring the colored light effect on the Balloon Analogue Risk Task (BART). *Journal of Environmental Psychology*, *57*, 73–82.

67. Bates, D., Mächler, M., Bolker, B., & Walker, S. (2014). Fitting linear mixed-effects models using lme4. *ArXiv Preprint ArXiv:1406.5823*.

68. Winter, B. (2013). Linear models and linear mixed effects models in R with linguistic applications. *ArXiv Preprint ArXiv:1308.5499*.

69. Gärling, T., Fang, D., Holmen, M., & Michaelsen, P. (2020). Financial risk-taking related to individual risk preference, social comparison and competition. *Review of Behavioral Finance*.

70. Sutton, S. (1987). Social-psychological Approaches to Understanding Addictive Behaviours: Attitude-behaviour and decision-making models. *British Journal of Addiction*, *82*(4), 355–370.

1.6 Appendix

1.6.1 Computer colors

Here are two sequences that used in this study as the true color of computer card for each round.

1.6.1.1 Risky colors

YELLOW, ORANGE, BLUE, RED, YELLOW, GREEN, RED, RED, RED, PURPLE, GREEN, BLUE, PURPLE, RED, ORANGE, ORANGE, PURPLE, BLUE, ORANGE, PURPLE, YELLOW, ORANGE, ORANGE, GREEN, YELLOW, RED, ORANGE, PURPLE, GREEN, YELLOW, YELLOW, YELLOW, BLUE, PURPLE, YELLOW, PURPLE, RED, GREEN, GREEN, RED, PURPLE, ORANGE, BLUE, BLUE, PURPLE, BLUE, BLUE, RED, ORANGE, BLUE,
BLUE, GREEN, YELLOW, ORANGE, GREEN, RED, GREEN, GREEN, PURPLE, YELLOW

1.6.1.2 Ambiguity colors

GREEN, ORANGE, RED, BLUE, BLUE, RED, YELLOW, ORANGE, ORANGE, GREEN, PURPLE, BLUE, ORANGE, ORANGE, GREEN, RED, ORANGE, ORANGE, GREEN, YELLOW, RED, RED, GREEN, YELLOW, GREEN, YELLOW, ORANGE, GREEN, BLUE, YELLOW, ORANGE, BLUE, GREEN, GREEN, PURPLE, GREEN, PURPLE, BLUE, RED, ORANGE,
ORANGE, RED, RED, GREEN, BLUE, RED, GREEN, PURPLE, GREEN, ORANGE, BLUE,
PURPLE, RED, BLUE, YELLOW, YELLOW, ORANGE, ORANGE, ORANGE, GREEN

1.6.2 Instructions and consent form

These are instruction forms which were used in this study in order for individual ambiguity, individual risk, social ambiguity and social risk.

Individual ambiguity

Dear Sir/Madam

Thank you for your participation. This text contains information about the game and the way of playing.

Please read the following text carefully and ask the researcher if there is anything that is not clear or if you need more information.

PREPARING TO PLAY

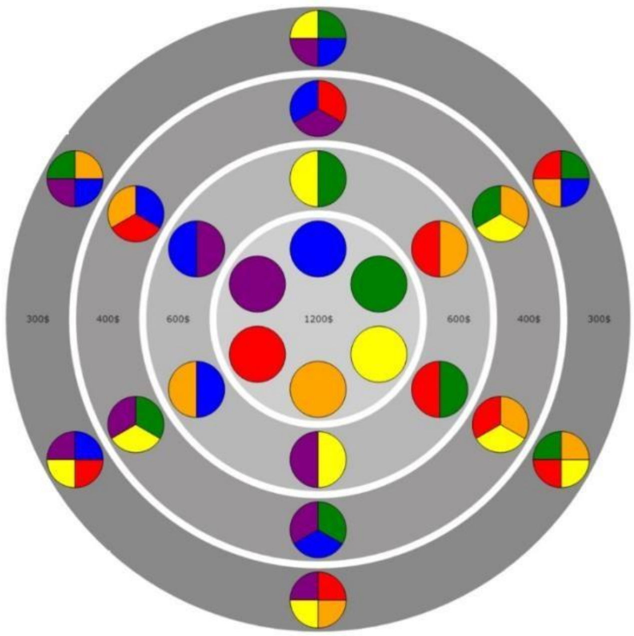
This game has three parts:

1- Individual information

   In this part, you enter your personal (full name, age, gender and CPR number) data. Your name and CPR information are used for payment purposes only.

2- Game Scene

   Your task in this game is to guess the color of a card, which is drawn from a deck of cards containing six different color cards (blue, green, purple, orange, yellow, red). Your job is to choose one option from a set of available options presented on the screen. The card is drawn from sixty cards in 6 decks of colors with different number of cards for



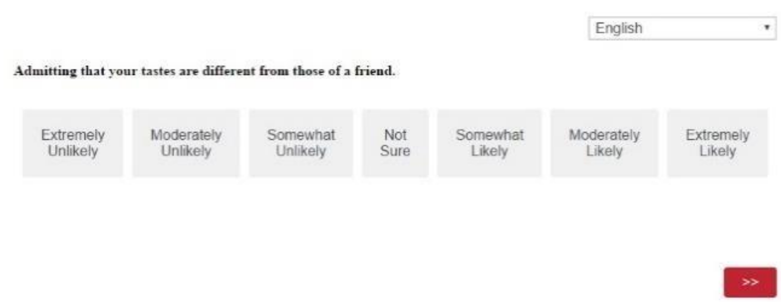
each deck. Therefore, we have 60 cards with a random combination of the colors. As depicted by above picture, there are four groups of colored options with the same score. Solo colors with 1200 points, two colors with 600, three colors with 400 and four colors with 300 points. It is possible for you to select one of them each time from the screen. For instance, you think that the color of the card that is drawn by the computer is red and choosing red by clicking on it from the solo colors. You will win 1200 points if your guess is true and you will lose 1200 points if it is not. Selecting from groups of multi colors means that your guessed color is one of these colors. For example if you choose the circle with three purple, green and yellow colors it means that you think the color of the computer card might be purple or green or yellow. Therefore, if the color is the same with one of these colors, you win 400 points and if it is not, you lose 400 points

and it happens the same manner for other options. You play the game for 50 rounds. After each choice, you see your result in the same shot as shown here.

3- Survey

After finishing of 50 rounds you see something like the below picture with your final score. Please copy this number on your receipt's blank space beside ¨----DKK¨. Then you should click on the green text ¨Now please complete this survey for entering into survey¨

The survey contains 30 questions with 7 scales that you should select one of them that explain your feelings more than others on that situation.



Individual risk

Dear Sir/Madam

Thank you for your participation. This text contains information about the game and the way of playing.

Please read the following text carefully and ask the researcher if there is anything that is not clear or if you need more information.

PREPARING TO PLAY

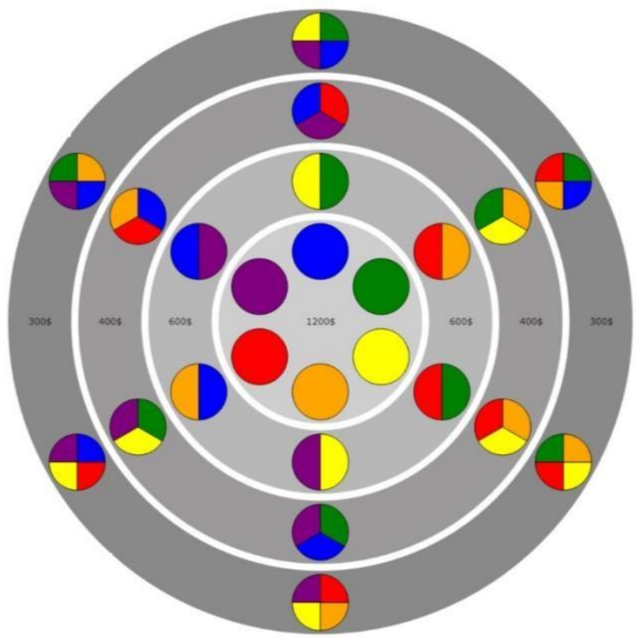
This game has three parts:

1- Individual information

In this part, you enter your personal (full name, age, gender and CPR number) data. Your name and CPR information are used for payment purposes only.

2- Game Scene

Your task in this game is to guess the color of a card, which is drawn from a deck of cards containing six different color cards (blue, green, purple, orange, yellow, red). Your job is to choose one option from a set of available options presented in the screen. The card is drawn from sixty cards in 6 decks of colors with the same number of cards for



each deck (10). Therefore, we have 60 cards with 10 red, 10 green, 10 blue, 10 purple and 10 yellow colors.

As depicted by above picture, there are four groups of colored options with the same score. Solo colors with 1200 points, two colors with 600, three colors with 400 and four colors with 300 points. It is possible for you to select one of them each time from the screen. For instance, you think that the color of the card that is drawn by the computer is red and choosing red by clicking on it from the solo colors. You will win 1200 points if your guess is true and you will lose 1200 points if it is not. Selecting from groups of multi colors means that your guessed color is one of these colors. For example if you choose the circle with three purple, green and yellow colors it means that you think the color of the computer card might be purple or green or yellow. Therefore, if the color is the

same with one of these colors, you win 400 points and if it is not, you lose 400 points and it happens the same manner for other options. You play the game for 50 rounds. After each choice, you see your result in the same shot as shown here.

3- Survey

After finishing of 50 rounds you see something like the below picture with your final score. Please copy this number on your receipt's blank space beside ¨----DKK¨. Then you should click on the green text ¨Now please complete this survey for entering into survey¨

The survey contains 30 questions with 7 scales that you should select one of them that explain your feelings more than others on that situation.

Social ambiguity

Dear Sir/Madam

Thank you for your participation. This text contains information about the game and the way of playing.

Please read the following text carefully and ask the researcher if there is anything that is not clear or if you need more information.

PREPARING TO PLAY

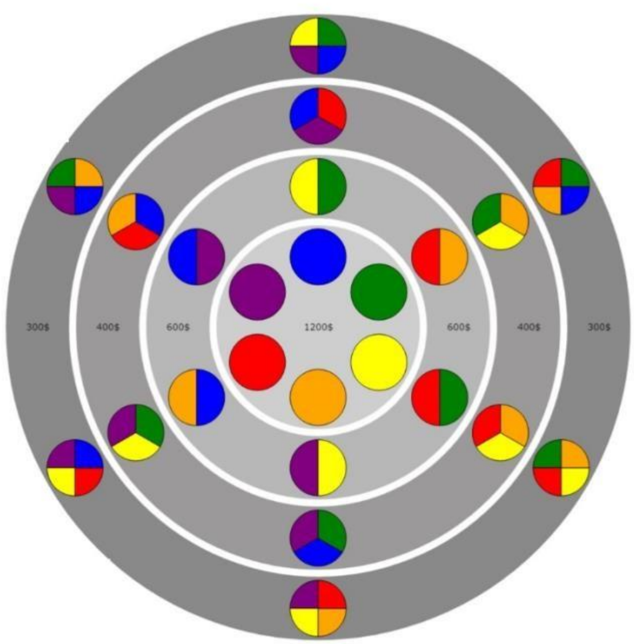
This game has four parts:

1- Individual information

    In this part, you enter your personal (full name, age, gender and CPR number) data. Your name and CPR information are used for payment purposes only.

2- Game Scene

    Your task in this game is to guess the color of a card, which is drawn from a deck of cards containing six different color cards (blue, green, purple, orange, yellow, red). Your job is to choose one option from a set of available options presented on the screen. The card is drawn from sixty cards in 6 decks of colors with different number of cards for



    each deck. Therefore, we have 60 cards with a random combination of the colors. As depicted by above picture, there are four groups of colored options with the same score. Solo colors with 1200 points, two colors with 600, three colors with 400 and four colors with 300 points. It is possible for you to select one of them each time from the screen. For instance, you think that the color of the card that is drawn by the computer is red and choosing red by clicking on it from the solo colors. You will win 1200 points if your guess is true and you will lose 1200 points if it is not. Selecting from groups of multi colors means that your guessed color is one of these colors. For example if you choose the circle with three purple, green and yellow colors it means that you think the color of the computer card might be purple or green or yellow. Therefore, if the color is the same with one of these colors, you win 400 points and if it is not, you lose 400 points

and it happens the same manner for other options. You play the game for 50 rounds. After each choice, you see your result in the same shot as shown here.

3- Social Scene

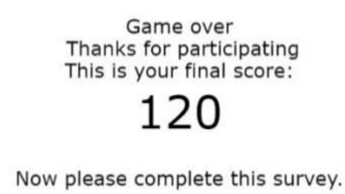
After first round, you are able to see results and choices of others that are presented with you in the lab. Below you could see the screenshot of this page. Here T means their scores for the previous round. If it is positive, it means gain and if it is negative, it means loss. By clicking on their emoji, you could see their choice, the color of the clicked one changes to gray, and that person's choice is shown by abbreviation of those colors. For example from the picture below P,B,G means that the selected player choice was from groups of three cards with the colors of Purple, Blue and Green and also was wrong. Looking to these information help you to get some ideas about the distribution of the computer color cards.

You are free to choose others as many as you want or also none of them. Note that this information can help you understand the distribution and patterns of the colors (which colors comes more?).

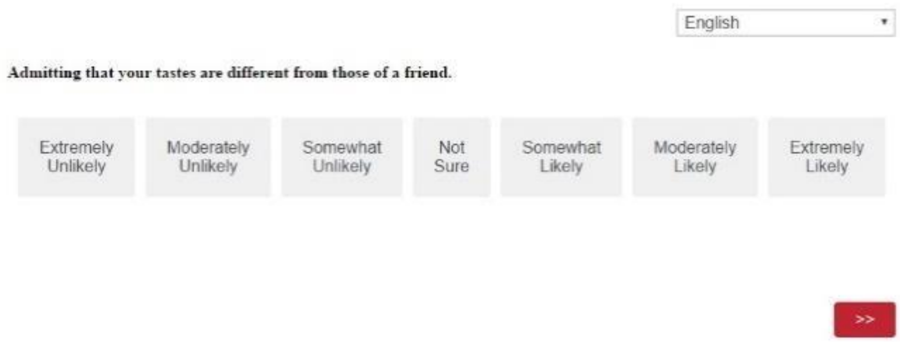
You must keep in mind that in social scene each click costs 10 points. It means that click on one-person costs 10 points, two-person 20 points and so on. These amounts decreases from your scores. When you have done, you should click on the red text below the page. ¨Click here when you are ready¨. Then it goes to the next round and so on for 50 rounds.

4- Survey

After finishing of 50 rounds you see something like the below picture with your final score. Please copy this number on your receipt's blank space beside ¨----DKK¨. Then you should click on the green text ¨Now please complete this survey for entering into survey¨



The survey contains 30 questions with 7 scales that you should select one of them that explain your feelings more than others on that situation.



Social risk

Dear Sir/Madam

Thank you for your participation. This text contains information about the game and the way of playing.

Please read the following text carefully and ask the researcher if there is anything that is not clear or if you need more information.

PREPARING TO PLAY

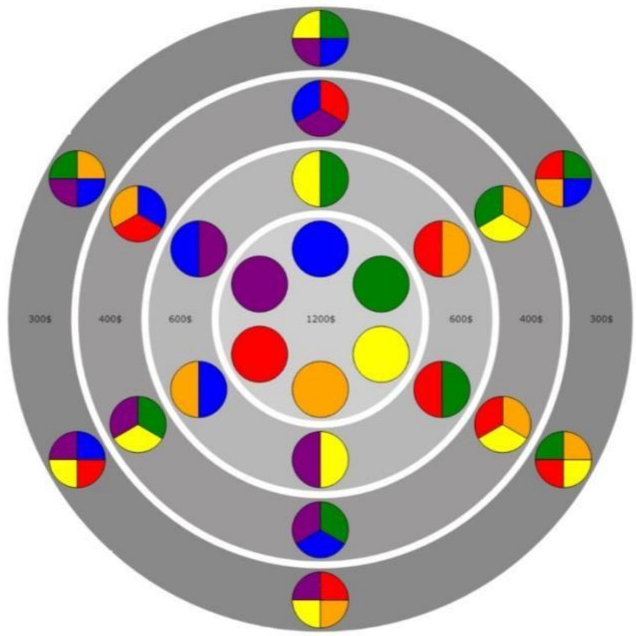
This game has four parts:

1- Individual information

   In this part, you enter your personal (full name, age, gender and CPR number) data. Your name and CPR information are used for payment purposes only.

2- Game Scene

   Your task in this game is to guess the color of a card, which is drawn from a deck of cards containing six different color cards (blue, green, purple, orange, yellow, red). Your job is to choose one option from a set of available options presented in the screen. The card is drawn from sixty cards in 6 decks of colors with the same number of cards for



each deck (10). Therefore, we have 60 cards with 10 red, 10 green, 10 blue, 10 purple and 10 yellow colors.

As depicted by above picture, there are four groups of colored options with the same score. Solo colors with 1200 points, two colors with 600, three colors with 400 and four colors with 300 points. It is possible for you to select one of them each time from the screen. For instance, you think that the color of the card that is drawn by the computer is red and choosing red by clicking on it from the solo colors. You will win 1200 points if your guess is true and you will lose 1200 points if it is not. Selecting from groups of multi colors means that your guessed color is one of these colors. For example if you choose the circle with three purple, green and yellow colors it means that you think the color of the computer card might be purple or green or yellow. Therefore, if the color is the

same with one of these colors, you win 400 points and if it is not, you lose 400 points and it happens the same manner for other options. You play the game for 50 rounds. After each choice, you see your result in the same shot as shown here.

3- Social Scene

After first round, you are able to see results and choices of others that are presented with you in the lab. Below you could see the screenshot of this page. Here T means their scores for the previous round. If it is positive, it means gain and if it is negative, it means loss. By clicking on their emoji, you could see their choice, the color of the clicked one changes to gray, and that person's choice is shown by abbreviation of those colors. For example from the picture below P,B,G means that the selected player choice was from groups of three cards with the colors of Purple, Blue and Green and also was wrong. Looking to these information help you to get some ideas about the distribution of the computer color cards.

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After finishing of 50 rounds you see something like the below picture with your final score. Please copy this number on your receipt's blank space beside ¨----DKK¨. Then you should click on the green text ¨Now please complete this survey for entering into survey¨

The survey contains 30 questions with 7 scales that you should select one of them that explain your feelings more than others on that situation.

Consent form

1. Title of research

You are invited to take part in the research study *Card Game* and we would like to ask you for your consent to participate in the study and for us to treat your data in agreement with data protection legislation. Before you decide to participate in this study, it is important that you understand why the research is being done and what it will involve. Please take the time to read the following information carefully. Please ask the researcher if there is anything that is not clear or if you need more information. The research project has been registered in Aarhus University's register of research projects processing personal information (journal number 2016-051- 000001, case number 1278). The research project has been approved by Cognition and Behavior Lab's Human Subjects Committee (project number 230).

2. Project description and aim of the study

We aim to investigate decision making as a dynamic process. Thus, we record the actions you perform in the card game. In this game you must guess the color of a card which is drawn from a deck of cards containing 6 different color cards and select among several options on the screen. You play against the rest of the participants who are in the lab. You could see their choice if you click on their icons. Your goal is to earn as much as you can.

3. Data controller, research group and principal investigator

Principal investigator: Fatemeh ShahrabiFarahani, ash@econ.au.dk

Data controller: Fatemeh ShahrabiFarahani, ash@econ.au.dk

Other researchers: Dan Mønster, danm@econ.au.dk

4. Study procedure

In the beginning of the experiment, we will ask for your name, CPR-number, age and gender. Your name and CPR-number will be used for payment purposes only, and will be separated from the other data immediately after the experiment is over. After this, you will be introduced to the card game, and play the game for 50 rounds. In the game you will place bets about what color card is chosen by the computer from a deck of cards containing cards of six different colors. If the card selected by the computer matches your bet, you will earn points, and if it does not match your bet, you will lose points. You will know how much you either win or lose after you make the decision. The game is played a total of 50 times. Your final pay will be calculated based on one randomly chosen trial from your entire game. In the worst-case scenario your possible score will be -1240 and in the best scenario it will be 1200. These scores will be converted to the final payment using this equation: Final payment=ceil(0.037*scores)+85

You could see your final payment which has already calculated by the above equation at the end of the game. 40 DKK is the lowest amount and 130 DKK is the highest amount of final payments. In the last part a questionnaire with 30 sentences will be displayed on the screen.

For each of them you must choose the answer which better describes your likelihood to engage in that activity.

5. Benefits and risks

The experiment involves no risks beyond those encountered in normal everyday life. You will receive 40 to 130 DKK based on your scores by participating in the experiment. The study is expected to last 20-30 minutes depending on your pace and the pace of the other participants.

6. Type of personal data and when it is deleted/anonymized

We process normal personal information in form of your CPR-number to make payments for participation in the study. Your personal data (CPR-numbers and Names) will be separated from other data from the research immediately after your participation. They will be deleted as soon as payments are finalized, which will be no later than two months after the study has taken place. Your results and behavior in the game are saved in anonymized form for further analysis.

7. Withdrawal of consent

Participation is voluntary and you may withdraw your consent at any time. This is done by contacting the data controller or the research assistant during the study, but the data cannot be withdrawn thereafter, because you can no longer be identified in the data.

Signature

I confirm to have received, read and understood the above information and that:

A. My participation is voluntary, and I may withdraw my consent and discontinue participation in the project at any time as specified in point 7. My refusal to participate will not result in any penalty.

B. By signing this agreement, I do not waive any legal rights or release Aarhus University, its agents, or you from liability for negligence.

C. I give my consent to statistical analysis of my personal data and to my participation as a subject in the study as described above.

____

(Signature and date)

____

(Name of participant, please complete in block capitals)

CHAPTER 2

Exploration-Exploitation Flow in Choice and Visual Sampling

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Aarhus University

Abstract

Exploration-exploitation is a common trade-off in human decision-making. This study examines the trade-off in two different contexts which have not been jointly investigated so far: choice and visual sampling. I introduce a new setup that allows for such independent measurement of visual exploration or exploitation, unlike previous studies that categorized visual exploration according to the chosen option in a choice task rather than measuring it independently. Two separate tasks are used to analyze exploration-exploitation in the two contexts. The first is a common two-armed bandit task that measures exploration-exploitation in choice. The second task is a novel setup for measuring visual exploration-exploitation. I run a within-subject design with 108 participants (*mean age* = 24.5, *standard deviation* = 4, female = 57). It is hypothesized that higher exploration in the choice context (first task) is correlated with higher exploration in the visual sampling context (second task), and exploratory behavior is consistent over these contexts. Results show a strong positive relationship between exploration in both tasks. Similarly, in an exploratory analysis of when participants stop exploring and start

exploiting in both tasks, a moderate positive relation is shown. Overall results confirm the hypothesis and show strong relation in exploratory behavior in both contexts.

Keywords: Dynamic decision-making, Risk-taking behavior, Eye tracking, Visual search, Exploration-Exploitation, Bandit, Behavioral consistency

2.1 Introduction

Adapting to complex and changing environments requires exploring novel knowledge domains or exploiting existing knowledge. Hence, decision-making often involves trade-offs between exploiting known knowledge and exploring the unknown [1,2]. This dilemma stems from the fact that exploring and exploiting are, in many cases, two mutually exclusive activities or can be viewed as the two extreme strategies. On one end, an individual or system that only explores (obtaining information about its environment to enhance future performance) pays the costs of obtaining new information without gaining the knowledge's benefits. At the other end, an individual or system that only exploits (uses existing knowledge only) lacks the capability to adapt to significant environmental changes and may be trapped in a sub-optimal outcome [3].
The two widely used paradigms in the exploration-exploitation field are Bandits and Foraging tasks [4–6]. People in bandit tasks must repeatedly choose between two or more options that differ in their expected reward while receiving probabilistic feedback from their choices [6,7]. The name "bandit task" derives from the analogy of a gambler drawing the arm of a slot machine (pejoratively known as a one-armed bandit) to figure out whether the draw results in winning money. There are variations in the bandit tasks by changing the number of arms, each paying different rewards that culminated in multiple actions. A participant must increase her outcome by choosing from these arms [6].

The bandit task is an ideal testbed for examining exploration-exploitation behavior because, unlike many other choice situations, it has an unambiguous way of identifying exploration vs. exploitation. In its classical form, known as the two-armed bandit, people face two options or 'arms' to choose. One arm pays a sure reward that does not change from round to round (fixed arm, subsequently), while the other arm generates an uncertain reward that can either be high or low compared to the known rewards (varied arm, henceforth) [8]. The task is similar to a range of real-life decision-making scenarios where humans sample from different options to find the best option to increase some outcome value. The optimal strategy in this decision-making problem depends only on the current beliefs about the different arms. This is captured by an index strategy [9] where a number is assigned to each arm, this number is updated after each trial based on the new information obtained, and the arm with the higher index is selected in any trial. This strategy says that once an individual has begun playing the arm producing a sure reward, she should stay there forever as no new information is being generated and hence the indices of the arms remain unchanged. Alternatively, if she employs the uncertain arm and a high payoff results, she should stay with that arm, since such a high payoff is positive news about the probability of the high reward and should lead her to increase the expected value associated with choosing of that arm; thus, the index on the uncertain arm increases [2,8].

There are several approaches to classifying chosen options in bandit tasks. For instance, in some studies, exploitation refers to choosing the option with the highest estimated value and exploration to selecting other options [10–12]. Steyvers, Lee and Wagenmakers [13] defined exploration as the number of times a participant chose an option with fewer successes and fewer failures than other alternatives, and they defined exploitation as the number of times a participant chose an alternative with more successes and more failures than another alternative.

Another prominent branch of the literature examines exploration-exploitation in foraging. It is based on a more naturalistic scenario in which humans or animals explore and exploit sources of food, either in a real-life or in a virtual setting [6,14]. In the foraging tasks, rewards are gathered by foraging in patches with different numbers of resources (mainly food). People can decide to exploit a specific patch or explore to find a new patch with more rewards. Exploiting a patch is correlated with consuming the resource of that patch, and after some time, the harvester should decide to stay with the patch or to look somewhere else [6,7].

The expected reward from the chosen option decreases as a result of depletion [6]. In this task, different options or patches can only be chosen in sequences, and a previously seen option cannot be revisited again. Studies measure the time subjects exploit a current resource before leaving it to search for a better one; this is also known as "patch leaving".

Here the tradeoff is between sticking with the best-known food resource (exploration) or searching for a potentially better food resource somewhere else (exploration) [14].

The exploitation-exploration trade-off has been studied in numerous other settings, such as, for example, clock task [15], in which participants select a clock hand at some desired times and earn different points. Here selecting the clock hand in different times labels as exploration, while selecting the clock hand at the same time defines as exploitation. The other example is "the alien game" [16] in which participants were asked to design artistic products by combining available shapes to sell to aliens. People explore the environment by sampling new combinations of shapes while sticking to the known familiar ones categorized as exploitation.

Overall, the literature suggests that individual differences in exploration could be thought of as a manifestation of their preference, much like other individual characteristics that describe how an individual goes about engaging with the environment [17]. This preference is the response pattern of the cognitive system to exploration-exploitation trade-offs and should be consistent across different situations, if it can truly be seen as a fixed characteristic or personality type [18]. This consistency can uncover the structure of general behavioral mechanisms [7].

We know a bit about how some individuals' characteristics correlate with the exploratory behavior in individual tasks [7,17], but very little about whether this behavior is consistent across different contexts for the same individual. To the best of my knowledge, at the time of writing this paper, there was only one study that compared exploration-exploitation behavior in different types of choice tasks to see if the propensity to explore is consistent across them. Helversen et al. (2018) [7] compared people's behavioral tendency in a foraging task with a sequential search for fish in several ponds, a multi-armed bandit task consisting of repeatedly choosing from a set of options, and a sequential choice task consisting of choosing a candidate from a pool of applicants [7].

In the foraging task, participants should catch as many fish as possible within 45 min. There were several ponds and participants could decide to stay or leave to a new pond, but leaving required time to find a new pond. There was a short and a long version of the task related to this time. The study varied the time required for switching ponds 15 seconds or 35 seconds. The bandit task had five arms. Participants played it in eight blocks of short and long versions in a within subject design. Short versions had 25 trials, and long versions 75 trials. The third task was a computerized secretary game, were participants needed to select the best secretary from a pool of applicants and could pursue exploration or exploitation strategies. The trial was finished once a secretary was chosen. The short version of the pool had 20 applicants and the long version 40 applicants. The authors did not find any significant association between the exploration-exploitation behavior of people in these three tasks. However, they found evidence of task-specific factors such as task domain (people have different approaches toward risk in health, finances, ethics, and etc. [7,20]), and horizon effect (number of trials [21]) that influence individual levels of exploration [7,20,21,22]. A possibly reason behind their finding of no consistency is as that the authors did not consider controlling for the task-specific factors and this could be the reason behind their findings in their study.

All we know about consistency in how individuals solve exploration-exploitation trade-offs in different choice tasks is the aforementioned study. In particular, there has been no previous attempt to assess whether exploration-exploitation is consistent across tasks, where the exploration-exploitation trade-off is about what option to choose in one task but characterized by a different context in the other task. The purpose of the current study is to fill this gap by comparing exploration-exploitation in a choice task with another task where exploration-exploitation is about whether to visually search for information or stop and choose among the sampled alternatives.

Risk preferences affect exploration-exploitation such that more risk-averse participants are more likely to choose to exploit than to explore in exploration-exploitation tasks [5,23,26]; thus, it is important to control for risk preferences. Indeed, we document small, significant correlation exploration-exploitations between risk preferences and exploration. Similarly, age and gender were also controlled.

What motivates using visual search as the context of interest in the second study, is that decision-making involves the process of collecting information and then deciding based on that information [27]. Often this process requires visual sampling of the environment to feed the cognitive system with decision-relevant information [28,29]. Eyes have an essential role in our cognition processes by visually sampling and controlling the visual input to the brain [30–32]. Fixations and saccades are two fundamental features of visual related studies. Fixation is the point during which the eyes are relatively stationary so that the visual system can take in detailed information about what is being looked at. A saccade is the rapid eye movement between fixations to move the eye-gaze from one point to another [33]. Ehinger, Kaufhold and König (2018) concluded that, while scanning a scene, resting the eye on a spot means that no new information input is sampled. Thus ongoing foveal processing during a fixation is an example of an exploitation process. In contrast, the initiation of saccades and thereby the inspection of the environment exemplifies an exploration process [32].

Research on exploration-exploitation trade-offs that incorporate process measures has mostly been restricted to examining the domain of choice behavior while tracking eye positions [30,32,34,35], interlinking choice with eye movement measures. Of these cases, Walker et al. (2019) [34] studied how uncertainty affects the exploration-exploitation in attention using a contextual two-armed bandit task. Options were described by some contextual features which were predictive of the rewards through initially unknown functions. The participants' role was to learn about the functional relationship between contexts and rewards and improve their decision strategy over time.

Visual attention was described by looking at the contextual features (cues) to provide predictions for the choice outcomes. Walker et al. (2019) [34] found evidence for the influence of uncertainty on the exploration-exploitation trade-off in both choice and attention. Walker et al.'s (2019) [34] study builds on Beesley et al. (2015) [35] where they investigated the same question using relevant/irrelevant cues by eye-gaze measurements in a two-choice task. Participants were presented with two over four possible cues on each trial and were required to select one of two possible responses. They were then told whether their response was correct or incorrect.

On each trial, two of the cues predicted the correct response as a relevant cue, and the other cues were irrelevant, providing no information on which response was correct. Participants were faced with these choices in two conditions. For participants in the certainty condition, the relationship between the predictive cue and the response's accuracy was perfect. The relationship between the predictive cue and the correct response was probabilistic for participants in the uncertainty condition. The authors found that participants in the certain group would, on average, spend more of the trial time looking at the predictive cue compared to the non-predictive cue. They argued that this is an exploitation strategy in a stable, certain environment.

Participants directed attention towards the best available cue to exploit their knowledge of the contingencies. It was also found that participants in the uncertain group spent more of the trial time looking at cues overall than the certain group participants. The authors argued that this reflected an exploration strategy that participants faced with an uncertain environment. Opting to spend more time attending to cues presumably attempted to gain new information from the cues that could allow for more accurate response selection in the future.

They found evidence for an influence of uncertainty on the exploration-exploitation trade-off in both choice and attention. In the choice domain, data suggested that responses were further away from the optimum under uncertainty compared to a certain condition. This response was similar in attending to cues. These findings support the idea of an exploration-exploitation in attention, and that uncertainty is a primary motivator for exploration in both choice and attention allocation.

Extant exploration-exploitation studies involving visual sampling have mainly focused on the actual decisions made, but not separately analyzed the visual sampling process behind a decision. One exception was Gameiro et al. (2017) 's study [36] on how exploration-exploitation changed by different image sizes. They used central tendency and entropy of the fixations by defining a decrease in the central tendency and an increase in entropy as exploration. They showed that visual exploration increased with an increase in image sizes [36].

There are two caveats with mentioned exploration-exploitation studies. Firstly, they presented subjects with few choice options only, making it hard to learn much about the exploration-exploitation trade-off in visual sampling because information can rapidly be scanned. Secondly, they specified visual sampling not by measuring fixation on options, but over something related to them like their cues as in the example mentioned above. Other studies labeled eye movements as exploratory or exploitative based on the properties of the selected option [30,32].

To know how uncertainty affects the choice and learning process, Stojić et al. (2020) [30] designed a task that forced participants to first see the options and analyze them, then select their preferred option within a limited time [30]. They ran two tasks with different variances of the reward distributions, using a six-armed bandit with options represented by a letter from the Gljagoljica alphabet. For a total of 60 trials, participants had to choose one of these alphabetic options. Based on the evidence that visual fixations facilitate working memory and memory retrieval operations, fixation time was taken to indicate learning. They fitted a computational model with two components of choice and learning to participants' behavior (Kalman filter and a lazy Kalman filter).

Results showed that both value and estimation uncertainty play a role in learning and choice. The fixation duration also increased toward high ranking options in the choice, which indicates relative fixation was affected by the same learning process that was guiding choices [30]. They conclude that visual fixations facilitate working-memory and memory retrieval operations. Looking at an option facilitates accumulating information about that option. It provides a mechanism through which relative fixation time before making a choice can have a direct influence on the decision and learning mechanisms [30]. So, they introduce a model including value, estimation uncertainty and relative fixation time before choice that explained actual choices.

Our study focuses on the exploration-exploitation behavior in choice and visual search and the relation between these contexts, not the parameters that affect this behavior. Ehinger, Kaufhold and König (2018) [32] investigated exploration-exploitation related to visual paradigms. They controlled the display time of a fixated bubble to test whether eye movements were generated more slowly with a short display time because the visual system is still in the exploitation phase. With a long display time, the visual system is ready to move on, and saccades are elicited more quickly whether people prefer to stay close to the current fixation or move on when they looked at a scene.

Their work was based on the idea of the two primary decision processes operating when looking at something. One of them is the decision about when to look, and the other is where to look. *Where* is based on salience characteristics of a scene like task, stimulus, geometric dependent features, and *when* is determined by the time available for the processing of the visual information available at the mentioned scene. Here, the ongoing foveal processing during a fixation is an example of an exploitation process. In contrast, the initiation of saccades and thereby the inspection of the environment resembles an exploration process.

It follows that the balance of these two processes determines whether we maintain the current gaze location or initiate a new saccade and consequently the distribution of fixation durations [32]. They investigated the exploration–exploitation dilemma in a guided viewing paradigm, where subjects saw only a small aperture of a scene (a bubble) at a time at each fixation. They exchanged the current bubble by up to five different bubbles at other parts of the underlying stimulus after this. The subjects then selected one of these bubbles via a saccade, and the unselected bubbles were removed.

The participants explored the image by repeating this process. This experimental design controls exploration-exploitation time by controlling the display time of the fixated bubble. The images in half of the trials were grayscale urban images. In contrast, in the other half, they used grayscale pink noise images to investigate how far these processes depend on the analyzed information. They found an exponential decrease of the time needed to choose the next fixation target depending on the time needed for processing the stimulus at the current fixation location which provides evidence for the exploration–exploitation dilemma in the decision process.

As mentioned, studies of exploration-exploitation in the field of decision-making mainly focus on choice. However, there are some studies in foraging that focus on visual search. As an example, Wolfe (2013) [37] investigated visual search behavior in a berry-picking foraging task.

There were 10 minutes for picking, and participants could choose a field from the three fields shown to them and then start to pick berries in their selected field. The number of berries differed in each field, and the participant could choose to leave the field for another whenever they wanted. It is shown that participants' behavior followed the

Marginal Value Theorem (MVT), which claims that an agent leaves a patch when instances from that patch drop below the average of the entire field. However, this was a visual search task, but it measured reaction times, not the actual visual searching behavior. Overall, eye movement studies on the foraging tasks mainly work on feature differences and their relation to visual attention [26,38].

Many studies have shown that choice and visual sampling are correlated [39–42], but they didn't investigate these behaviors in exploration-exploitation behavior.

Taking into consideration the background mentioned above and the limitations observed in the literature, this study seeks to analyze exploration-exploitation related behavioral flow in different contexts of choice and visual sampling. In the real world, people face tasks that they have to explore visually to collect information in order to make a decision. This was the driving factor in designing the experiment. One could argue that a more direct measure of exploration-exploitation in this setting is to consider the trade-off between spending resources to explore by sampling more information (sampling involves costs in terms of cognitive resources and time) or to exploit by directly proceeding to making a decision based on the existing information.

The aim of this study is to directly investigate this process of visual search (eye movement) and then correlating the exploration-exploitation behavior in this context with exploration-exploitation behavior in the choice context captured by a standard bandit task.

Unlike previous studies that categorized visual exploration according to the chosen option in a choice task, we planned to measure it independently. Thus, we chose the two-armed bandit for measuring exploration-exploitation in monetary choice context, which is accepted and widely used due to its simplicity to learn by the participants and also classifying exploratory arm. Bandits with more arms needed more sophisticated algorithms to label exploration vs. exploitation. We follow Banks' bandit step by step except having unlimited rounds. It makes reproduction easy and salient. However, as this task has only two options, there is no added value to do the visual search for this task as there is no search in only two options.

It is not possible to tile the screen page with the bandit's arms as it eliminates learning factor as participants do not have the time and opportunity to learn patterns behind that number of arms. However, if the tiles consist of obvious monetary values, it will be more salient and straightforward to do a visual search over their values to find the higher ones. It is similar to a foraging task in searching between options, but the difference is options are monetary, not limited in resources, not in different colors, and also, they are not similar in definition of exploratory and exploitative behavior.

As in foraging tasks, staying in a field and choosing from its food source is classified as exploitation while traveling between the fields is exploration while in our new task, exploration is looking for a new high value over tiles vs. exploitation, which is looking at a safe option since its value has been seen before. It is a task to measure participants' exploration-exploitation based on the option they look at, not a measurement and labeling eye movement based on the final choice as it is in the literature.

The reason behind choosing two very different tasks was that it gives a convincing test of whether people in a consistent manner solve the structurally similar underlying exploration-exploitation tradeoffs. If tasks were very similar, one could not separate behavioral consistency because of solving some underlying structural problem in a similar way. We expect to see similar dominant exploration or exploitation behavior in the choice and visual sampling.

2.2 Method

2.2.1 Experimental design

This experiment was performed across two different tasks in a within-subject counterbalanced design to control for possible order effects. Each participant performed both tasks while half of the participants received task one first, followed by task two; the other half received task two first, followed by task one. Participants received incentivized compensation according to how many points they scored in one of the two tasks (selected randomly), converted to real money using a known conversion factor. As it is mentioned, one of the tasks was the classical two-armed bandit task [8], where the exploration-exploitation trade-off is about choices made in several rounds. One of the options (arms) pays a fixed amount in this task, while the other pays a probability-based amount. Choosing the arm with the fixed, known amount in a round was defined as exploitation, and choosing the other arm was defined as exploration.

The second task was focused on visual exploration-exploitation in a complex outcome space investigated using eye movements. Here the participant's role was to collect points by choosing options presented in this space, having only limited time. This space included a known option in the center and probabilistic, visually mixed options in the screen's surrounding parts. These visually mixed options contained two types of options, ones with points higher than the center option, and ones with points lower than that. These points were assigned randomly to each option. The task produced a visual exploration-exploitation trade-off between finding a higher value or staying with the center value. Here, the number of visual fixations on surrounding options was defined as exploration. Using these two tasks, exploration-exploitation was investigated in the two contexts of choice and visual search. We postpone discussion of further details of these tasks until the next subsections and instead first focus on some points related to the study's overall design.

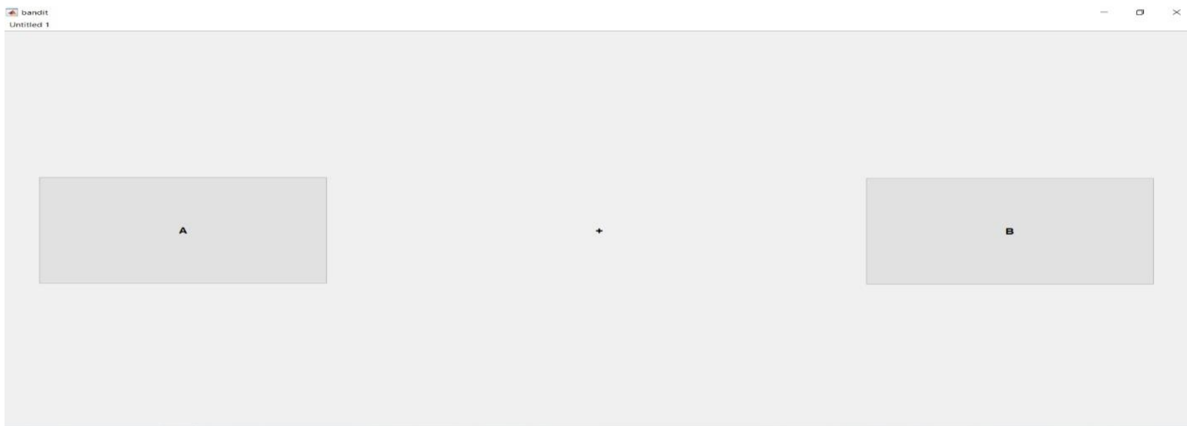
For the experimental design it is relevant to consider whether or not to vary the domain of the tasks. Exploration-exploitation is a risky behavior [19], and some evidence exists that risk preferences differ across domains (e.g., people have different approaches toward risk in health, financial, or ethical dimensions [7,20]). The other design features of exploration-exploitation tasks affect the possibility of order effects and horizon effects [21,22] and concern controlling for risk preferences [5,7,23], age, and gender effects [19,24]. Running subsequent tasks in a within-subject design potentially leads to order effects. The counterbalancing method varies the order of conditions such that each task is presented first to one set of participants, allowing to test for such order effects. In particular, the absence of an order effect means that fatigue or learning does not affect participants' behavior in a way that influences findings. According to Wilson et al.'s Horizon study (2014) [21], the number of trials affects the rate of exploration. With the longer time horizon, the value of exploring uncertain option gets higher as increased in a number of times an option is observed, decreases its uncertainty [22,25], and hence horizon should be the same for both tasks. More risk-averse, women and older participants are more likely to choose to exploit than to explore in exploration-exploitation tasks [5,23,26]. The within-subject design needs to control these factors in the analysis part. Besides, we obtain a survey-based measure of risk preferences that can be used as a control.

Due to differences in the structure and the payout across the two tasks, performance in one was not expected to affect the other. Nevertheless, we implemented a procedure to avoid possible confounds due to hedging behavior [24]. Specifically, at the end of the experiment, one task was randomly selected to be used for payments. Paying randomly based on the outcome of one of these tasks meant that a participant could not compensate good performance in one task for bad performance in the other task and that performing well in the first task did not allow participants to relax and concentrate less on the second task.

2.2.1.1 The bandit task: Exploration-exploitation in choice

One of our study tasks was a classical bandit problem with one known and one unknown arm, similar to the study of Banks, Olson and Porter (1997) [8]. A screenshot of this task is shown in Figure 2.1. One arm (A) offered a certain fixed value any time it was selected (845 points), and the other (B) offered a good or bad value, with a fixed prior probability of the arm being good. This probability was set to .5 here and meant that 50 percent of the time this arm was bad, and 50 percent of the time it was good. This experiment ran for 10 rounds and was repeated for 20 periods. Each period could be good or bad, and 10 periods were good and 10 periods were bad. Rounds belonging to a good period had the chance of earning 1690 points 90% of the time and nothing 10% of the time, while if they belonged to a bad period, they provided nothing 90% of the time and 1690 points otherwise. Thus, the expected payoff for choosing arm B and A was 845 per round.

Figure 2.1: Two-armed Bandit.



Notes: The left option (A) is the fixed option which always pays 845 points, and the right option (B) pays 1690 or 0 with some probabilities

These values were chosen to be congruent with the probabilities used in Banks, Olson and Porter's (1997) [8] bandit task and range of outcome in the second task. Considering the above rules, to make the outcome behind the uncertain arm, a sequence with a length of 100 containing 50 zeros and 50 ones was made. One random element was chosen from this sequence with replacement, and this was repeated 20 times to satisfy the first condition of having a bad or good outcome with a 50% probability for each period.

Two arrays with the length of 100 of high or low values were constructed to generate values for good and bad outcomes. A good array had 90 high and 10 low values, and a bad array had 10 high and 90 low values. For each period, a value selected at random from the sequence of zeros and ones was checked. If it was 1, a sample was drawn from the good array with replacement, and it was repeated 10 times to make one round from the good array. If the selected value from the sequence was 0, a sample was drawn from the bad array with replacement, and it was repeated 10 times to make one round.

This procedure was continued until all variables of the sequence were selected, which was equal to the number of periods (20). Thus, the resulting outcome was an array with a length of 10 rounds and 20 periods. To have a pre-randomized payoff for the uncertain arm, this process was repeated twice to have two different sequences for the outcome behind that arm. These sequences were drawn before the experiment and used across sessions. Half of the participants in each counterbalanced group received the first sequence, and the other half received the second sequence for the uncertain arm. It served to have both variations for different outcomes in participants' behavior and the similarity of the outcome to control for effect of losing or winning in the previous choice.

Participants knew about probabilities and values. After finishing the 10 rounds and 20 periods, the participants saw their overall results. The total payoff for the task was the sum of the payoffs in each period. Based on Wilson et al.'s horizon study (2014) [21,43], to have a congruent measure of exploration-exploitation in both tasks, the number of trials was set to a similar value. This value was 20 as the number of periods in both tasks. To have a consistent measurement of exploration in both tasks, 10 was selected as the number of rounds within each period in this task. The reason for choosing 10 will be explained in the visual task.

2.2.1.2 The visual task: Exploration-Exploitation in visual search

Existing studies have considered visual exploration-exploitation as equivalent to exploration-exploitation in choice [30,32,34,35]. The current study's innovation is to directly examine visual exploration-exploitation by using a task with two different groups of options that participants can choose from. The first group was an option placed in the center of the screen which paid a number of points in the range [1350,1650] where each integer number in the range had the same probability of being selected. The second group, placed in the surroundings, contained 132 options[7] for which values were randomly determined at the start of a round and among which the participant could search for a high value.

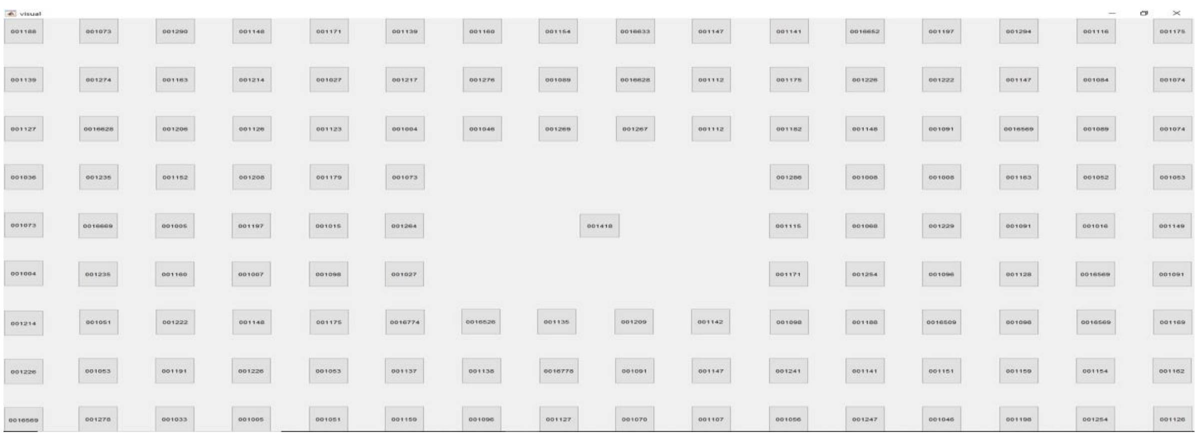
Each option was formed as one Region Of Interest (ROI) for visual investigation[8]. Of the surrounding options, 10% of them (13) paid more points than the center option, and

[7] The reason behind choosing 132 options is explained in the last paragraph of this section

[8] ROIs or AOIs are defined as areas in the stimulus space in which the activity of the eyes is investigated [44].

90% of them (119) paid fewer points than the center option. The 13 higher values were drawn from the range [16600,16900] points, and the 119 lower values were drawn from the range [1000,1300] points. The reason behind choosing these ranges of values was to remove interference between these ranges and their expected values. Both ranges and reward expectations for that range satisfy the sequence of being higher or lower. Figure 2.2 shows a screenshot of one period of this task.

Figure 2.2: Visual task



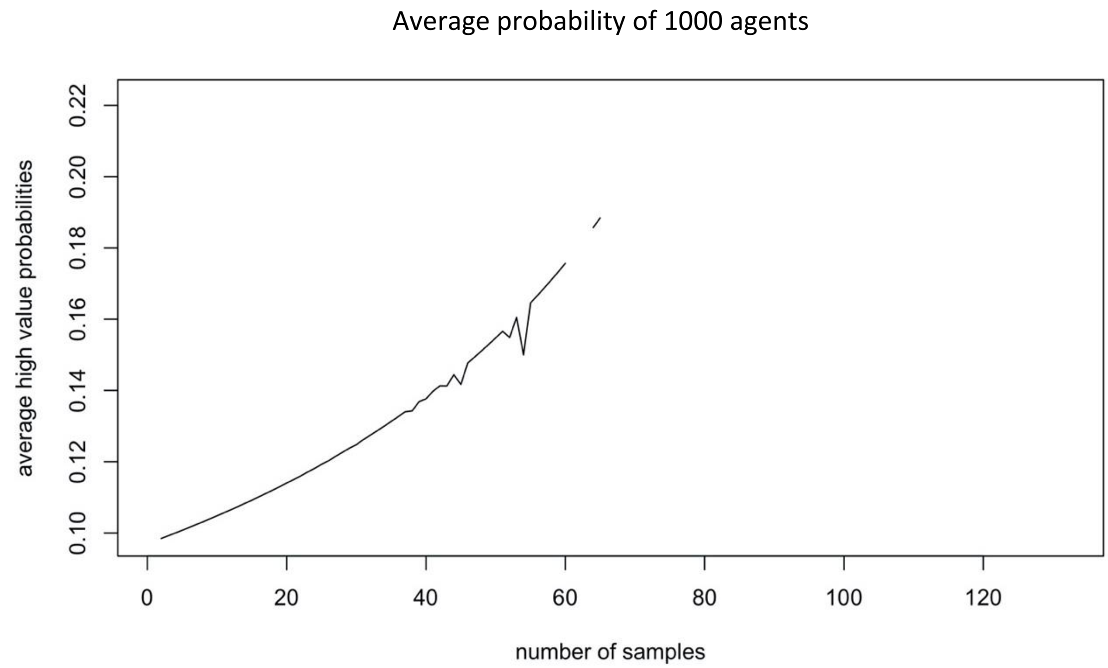
Notes: The centered option's value was lower than 10% of the surrounding values and higher than 90% of them.

That only about 10 percent of values exceeded the center option ensured that finding the high values was time-consuming and challenging. We label as exploration the number of values of options visually sampled once in the surroundings. Participants knew that the center option provided a fallback option with a relatively high value; thus, we labeled it as exploitation. Additionally, returning to the highest value identified before was also labeled as exploitation. The exploration-exploitation trade-off is between starting/continuing to sample values or sticking with either the fallback center option or with the current highest value identified.

The value of the option selected determined the task's outcome for the current period. The center value was placed in the center of the screen to make exploitation salient compared to exploration over the surrounding options. This ensures that we measure deliberate exploration instead of noise from a participant trying to figure out the screen layout. To create an actual cost of exploration, participants faced time pressure. The number of points awarded for the centered option was decreased by 10 points every 3 second, and there was a total of 15 seconds for choosing one option and finishing a period. If no choice was made within 15 seconds, the system chose 0 points for that period, and the next period started. The rationale for decreasing the center option's value is best illustrated by considering the initial choice faced by a decision-maker. She faces the choice between the center option or sampling up to 10 options in the surroundings. The 3-second window was set based on a pilot study where participants on average fixated .3 seconds to sample one option in our design visually. Hence, the time window allowed to sample around 10 options before the value of the center option decreased. This setup is congruent with the 10 rounds in the bandit task as it limits the number of explorations in both tasks. One with the number of rounds and one with the time limitation.

A myopic decision-maker would compute the expected value from sampling one more point than choosing the center option/the best option so far identified. For instance, if the value for the center option was 1350, the expected value of a first fixation being higher than the center (if the first fixation is on 16900) is $(13/132) \times (16900) = 1664.39$ which is higher than the expectation of the center value. This overstates the attractiveness of exploration because there is an option value from being able to continue to search after the first value.

Figure 2.3: Probability of finding a good option over number of sampling.



Notes: Using a simulation of 1000 agents over the number of options, the probability of finding a high value is shown for searching through 1 to 132 options. The horizontal axis shows the number of searched options, and the vertical axis is the probability of finding a high value within these options.

To calculate probabilities of seen options being high for one round, a Monte Carlo simulation was used. This worked by choosing a sample from a range of numbers repeatedly without replacement, from seeing 1 sample to 132 samples. This sampling was repeated 1000 times and calculated probability for high captured samples by averaging over the total number of captured higher values. It showed a slight decrease after seeing 50 options (Figure 2.3). That was the reason behind choosing 50 options or 15 seconds as the limited time of each period. Increasing probability shows higher expectation in searching the field; however, after almost 70 options, there is no chance of finding higher options due to sampling without replacement.

Each option's points were fresh random draws over mentioned ranges of high and low values for each 20 periods. Two sequences of these values were used to keep hold of all the participants using the counterbalancing method. These sessions differed in the tokens' value and position, but not in the ranges that the tokens selected.

This task's final points were the sum of the points over all of these 20 periods. To make it harder to find a high number and to make sure participants use their overt attention to search through options [45], two leading zeros were added to the value labels for each option,

e.g., 001240 for an option worth 1240 points. Thereby numbers blend in with each other and are harder to distinguish without focusing on them. Based on the required area for a digit which is .1cm^2, each option with the maximum of 7 digits required .7cm^2 space. To ensure having a good precision, it is recommended to add a margin from 1 degree to 1.5 degree of visual angle around the object in defining ROIs for the EyeLink eye-tracker [46,47]. Thus, 1 cm was added to both the width and height of the mentioned required size. It resulted in a square ROI with the length of 1.7, which divided the screen with the resolution of 1920×1080 into 30 × 17 cm rectangular boxes[9]. Options were placed with a distance of one option beside each other to be separable. There were also 62 distance options around the center option to make it easily recognizable. So regarding mentioned points and the possible space to put the options, a total of 132 surrounding options (ROIs) were placed on the visual task space.

2.3 Theoretical background and hypotheses

2.3.1 Theory-Bandit task

Participants' initial information about an arm's actual type is the probability of the uncertain arm being the good type and the certain arm's value. They update their beliefs after every choice concerning reward probabilities. The optimal strategy is described by a comparison between current and updated beliefs. In this comparison, the option with higher expectation will be selected as the optimal choice [8]. As Gittins and Jones described [9], individuals update their beliefs based on the information they get with sampling from arms. They assign index numbers to the arms that depend only on the history of values observed for that arm. The index only changes if the value of the arm is not constant. The optimal strategy is to select the arm with the highest index.

[9] One pixel is equal to 0.0265 cm, thus a 1920×1080 pixels' monitor is equal to 50.88×28.6 cm^2

Doing this, once someone has begun playing the arm producing the fixed payoff, she should remain there forever because no new information is being generated. Alternatively, if she employs the uncertain arm and a high payoff appears, she should also remain with that arm as the uncertain arm's index then increases. A high payoff leads her to increase the belief about the future payoff from that arm's continual play. More generally, the theory predicts that an individual has a critical belief about the uncertain arm. If her current belief about the uncertain arm being "good" is above this level, she should employ that arm in the current period. If her belief is below this level, she should play the certain arm and remain there.

2.3.2 Theory-Visual task

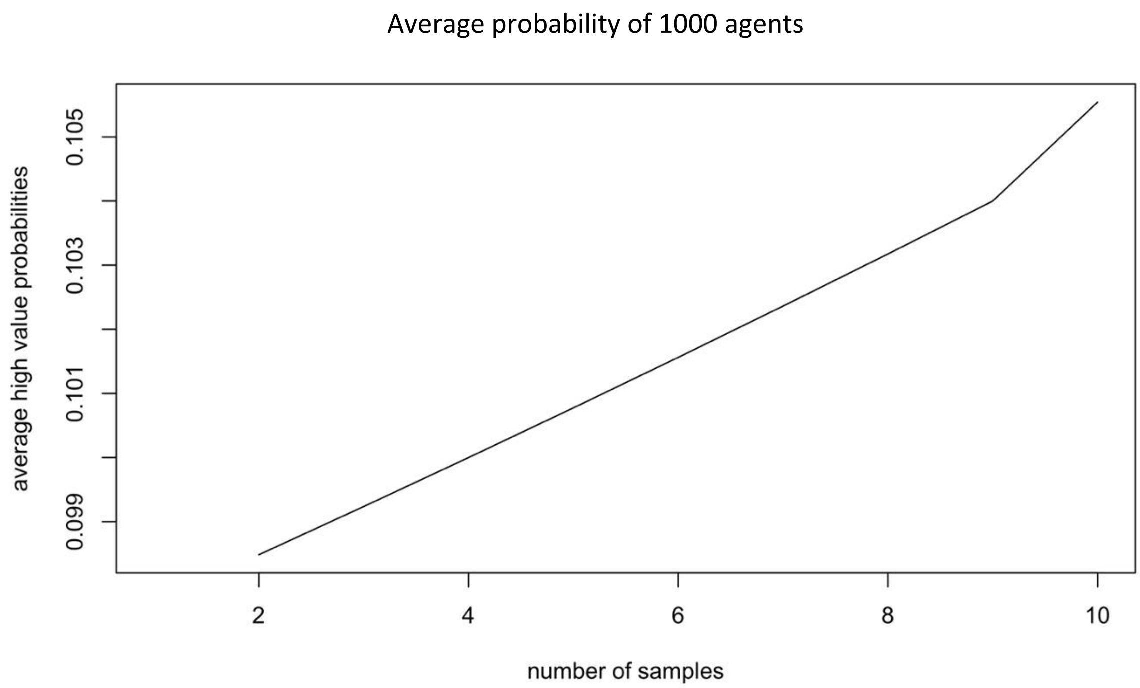
Participants faced a dilemma of whether to explore more and find a higher value or exploit the center option/best known option at that time point. The difference between expected payoffs of the surrounding options and the center option at the start of the round shows that it has a higher expected payoff to search the surrounding options for higher payoffs than to choose the sure fixed value. Thus, related to the above example of a myopic decision-maker, the prediction was that participants tend to start with visual exploration since the expectation of exploration was higher.

Given that the central value is a salient fallback option about which the decision maker knows that it has a relatively high value, it is the natural option to choose sampling first. Thus, our prediction is that the center value will be sampled first and be relevant for comparing with the next option sampled (exploration = 1), if any visual exploration occurs.

In the second exploration, the decision maker samples another point and tries to find the higher options by choosing a nearby option from the whole screen. If this value was lower than the previous one, then the decision-maker should continue to sample because she found it optimal to sample the last point, and the chance of sampling from the high value range has increased. For example, for the first exploration there is a 13/132 chance of a number from the high value range, which increases to 13/131 after sampling a number from the low value range. If the value of the center option is the highest value sampled so far, it is also relevant whether the new sampling will be possible within the 3-second window before the center option decreases by 10 points. On the other hand, if the sampled value was higher than the previous best value, it becomes the new best value.

Figure 2.4 depicts probability of sampling a point in the high value range by considering a restriction in time and hence choosing an option before reaching the threshold (3 *seconds*). It is only possible to search 10 points in this amount of time.

Figure 2.4: Probability of finding a good option over a number of samplings in first 3 seconds.



Notes: Using a simulation of 1000 agents over a number of options, probability of finding a high value is shown for searching through 1 to 10 options. The horizontal axis shows the number of searched options, and the vertical axis is the probability of finding a high value over these options.

Using a myopic strategy, the number of times we expect a risk-neutral decision-maker to explore and its resulting payoff in one round was simulated. By simplifying the performance of the decision-maker, this strategy compares the one-step-ahead expected value to the current highest known value. This strategy is explained in the Appendix section. While this is a reasonable prediction for how an actual participant might approach the problem, note that it is not the solution for the optimal strategy. A sophisticated agent would explore more than predicted by the myopic strategy because of the option value of continuing to search. On the other hand, risk aversion and time pressure from decreasing the ex-ante known value will work in the other direction and lead to less exploration. For our purposes, however, the example illustrates the direction of the overall driving forces, and a precise characterization of the optimal strategy is of lesser importance.

2.3.3 Hypotheses

As mentioned, we do not know whether people consistently approach exploration-exploitation because studies look at tasks one by one but do not correlate what individuals do across tasks. We would expect consistency based on the existing theoretical paradigms, but whether this holds is an open empirical question. As an analogy: in economics, a very prominent theory of inequity aversion is able to make sense of behavior in a wide range of choice situations considered on their own. But once one started studying whether within an individual the parameters of the model implied by the choices in one task could be used to predict choices in another task, one did not find very consistent behavior [48]. That is, a theory looking right in studies of tasks looked at in isolation might turn out to be a bad theory once taken seriously as a model that should predict consistent behavior within an individual across different choice situations.

Both of the described tasks measure exploration-exploitation behavior in a within-subject design but with different contexts. As these are the outcome of one inferential system, we expect to see a positive relation between them. So, it is hypothesized that exploration in the choice context (first task) is positively correlated with exploration in the visual sampling context (second task).

2.4 Experimental procedure

The experimental procedure was structured as follows: After participants signed up for the study, they received an identification code via email to link their behavior in the experiment in an anonymous manner. They received a link to a questionnaire to rate their usual risk-taking behavior. Their emails were deleted after data collection was finished.

Upon entering the laboratory, participants received a consent form and instructions about the first task on paper. They were given ample time to read them and ask questions. There were also some written questions to make sure they understood the task completely. Instruction for the bandit task is similar to the Banks, Olson and Porter (1997) [8] task. After signing the consent form, a calibration procedure was performed. With the researcher's help, a convenient position was found for them in front of the computer. After that, they entered their identification code, age and gender in a form shown on the screen. After this part, they were asked to follow a black dot on the screen to calibrate the eye tracker. A 13-point calibration was used. If the accuracy at fixated positions was acceptable, validation and drift check steps were then performed before the first experimental task started.

The order in which both tasks were performed was determined before participants came to the laboratory. Half of the participants performed the bandit task first followed by the visual task, while the other half performed the tasks in the opposite order. There was a calibration stage before each task, and after the first task, there was a 3 minutes rest period. The bandit task process started with choosing from its two options, as shown in Figure 2.1. There were 20 periods with the probability-based outcome for arm B and fixed outcome for arm A. Each period had 10 rounds. After each choice, the mouse pointer returned to the center of the screen, and after every 10 rounds, the value behind arm B was charged to the other pre-randomized value, which could be of the good or bad type.

After this task was finished, the outcome was displayed on the screen and recorded by the researcher. This token could be 20×10×1690 = 338000 tokens for the best-case scenario where all values behind arm B paid the highest outcome. The number of the visual task's periods was equal to the bandit (both 20 periods). Each period was finished by choosing a value from the screen, then the mouse pointer returning to the center. After finishing the 20 periods, the total score of this task was displayed on the screen. This score could be 20 × 16900 = 338000 tokens in the best-case scenario where all higher values were found for each period. Again, the result was recorded by the researcher.

The last part, which was the calculation of the final payment, was done by entering two tasks' outcomes on the researcher's related form. Behind this form was a function that randomly chose one task's tokens and converted them into Danish kroner (DKK).

This selected score was converted to the final payment using an exchange rate of .0003 DKK/point plus a show-up fee of 45 DKK, and it was shown on the screen. The payment was 45 DKK in the worst-case scenario and 145 DKK in the best-case scenario.

2.4.1 Survey

Responding to survey questions, unlike behavior, is not incentivized, so economists rarely rely on them [49]. They are hard to interpret and time-consuming to be answered. However, based on what Dohmen et al. (2011) introduced and validated [49], one general question about risk-taking generates the best all-around predictor of risky behavior. Here, to have a sense of participants' risk preferences, one simple question was used and asked at least one day before doing the lab experiment. The question, which was the same as what Dohmen et al. (2011) [49] suggested, was:" How do you see yourself: Are you generally a person who is fully prepared to take risks, or do you try to avoid taking risks? Please tick a box on the scale where the value 0 means: 'not at all willing to take risks', and the value 10 means 'very willing to take risks'." [49].

2.5 Results

2.5.1 Outcome variables: analysis based on exploration rate

We obtain a measure of exploration for each of the two tasks that captures how a participant approached the exploration-exploitation trade-off. In the bandit task, exploration is defined as the number of times arm B was chosen:

$$\text{exploration}_{Bit} = \text{the number of times arm B was chosen in period } t,$$

where t is the period $\in \{1,...,20\}$ and i identifies the participant. Each period involved 10 rounds. Thus, exploration_{Bit} takes a value between 0 and 10.

In the visual task, exploration is defined as the number of options that is visually sampled before making a choice, deducting the center option and the options sampled more than once:

$exploration_{Vit}$ = the number of options visually fixated at least once in period t,

where t is the period $\in \{1,...,20\}$ and i identifies the participant. In each period, a participant could sample up to almost 50 options if we consider .3 seconds time for sampling and a time limit of 15 seconds for each period. However, it could be higher or lower depending on participants' pace in sampling. Thus, $exploration_{Vit}$ could take a value between 0 and almost 50.

We were interested in making conclusions about how exploration in the bandit task was related to exploration in the visual task in a within-subject design. This design was considered for testing consistency in exploration-exploitation behavior across two tasks. However, in a within subject design it is necessary to control variability in the analysis part by controlling effective factors on the fixed effects, despite the between-subject design that controls variation using random allocation [50].

Risk preferences, age and gender affect risk-taking and also exploration-exploitation. Such that more risk-averse, females and older participants are more likely to choose to exploit than to explore [5,23,26].

As participants bring these factors to the test, and they may affect the average outcome, this heterogeneity should be controlled [50,51]. So, we controlled these two factors of gender and risk preferences, but not the age because all the participant came from similar age range (24.5 +/- 4).

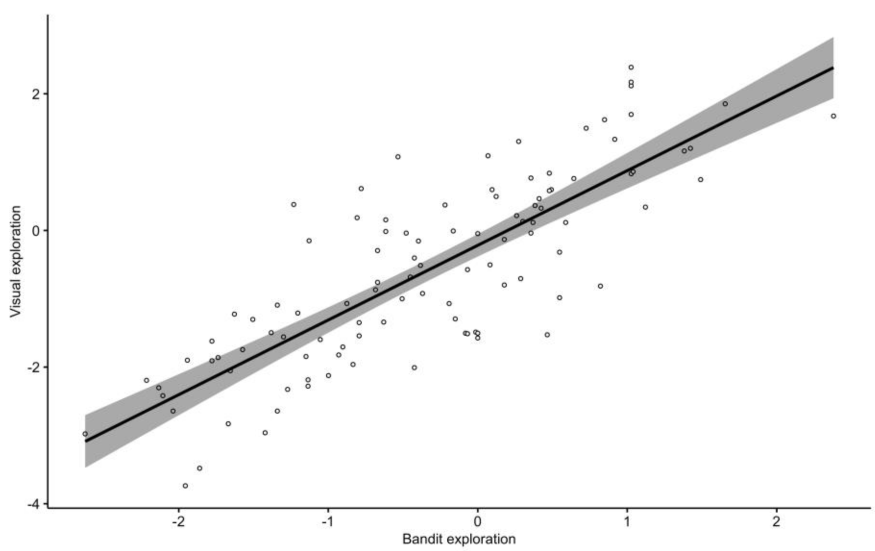
As mentioned, fixed effects were employed as proxies for the degree to which a participant can be classified as someone prone to exploration in a particular task, controlling for gender and risk preferences which possibly would explain exploration based on observable characteristics and captured any possible influence they might have had. To do so, the idea from the worker-firm matching literature of using fixed effects to proxy for unobserved worker or firm types (Abowd et al.[51]) was applied.

The idea from the analysis method of Abowd, Kramarz, and Margolis's (1999)[51] study was using the fixed effect to control for a number of covariates as proxies to capture heterogeneity. Fixed effects were employed as proxies for the degree to which a participant can be classified as someone prone to exploration in a particular task, controlling for gender and risk which possibly would explain exploration based on observable characteristics. The stats package of R software was used for building this model.

$$exploration_{Bit} = \alpha \times gender_i + \beta \times risk_i + \gamma_{it} + \varepsilon \qquad (1)$$

Eq. 1 gave the effect of covariates (gender and risk) on standardized exploration for the bandit task using the mentioned method. This regression was also run for the visual task (*exploration*$_{Vi}$). γ_{it} keeps individual intercepts, and ε is the error term. By removing the effect of gender and risk as the proxy effect, each person (i) in each task had a fixed intercept (γ_{it}), which was the unexplained part of the dependent variables. The relation between these intercepts of both tasks are shown in the scatter plot of Figure 2.5. There was a positive correlation between exploration rates in the two tasks, such that a unit increase in visual exploration increased bandit exploration by .8, $r(106) = .81$, $p < .0001$.

Figure 2.5: Scatter plot of both tasks' exploration



Notes: The x-axis depicts exploration in the bandit task, and the and the y-axis exploration in the visual task. There is a significant positive correlation between the two measures.

2.5.2 Exploratory analysis based on cutpoints

In the bandit task, according to the theory, once a person switches from arm B (exploration) to arm A (exploitation), arm A should be chosen ever after [8]. An alternative measure of exploration hence is to look at the period when a person switches from arm B to arm A (a so-called cutpoint). Of course, in the data, people might switch back and forth, which is why Banks, Olson and Porter (1997) [8] define a best cutpoint measure to investigate their strategy.

Similarly, for the visual task, a cutpoint is also defined and calculated. The cutpoint value started at zero in the bandit problem at the beginning of the task, then it increased by one if arm B was selected and resulted in a good draw, but if it was a bad draw, the cutpoint decreased by one. Otherwise, which was the selection of arm A, the cutpoint remained unchanged. In the visual task, the cutpoint was zero when the task was started. It was increased by one when the fixation was over a higher value. If it was over a lower value, it was decreased by one. Otherwise, by looking at the centered option, it remained unchanged. The cutpoint with the highest length of occurrence was chosen to best describe the point of deviation in each period related to staying in the arm A/center option.

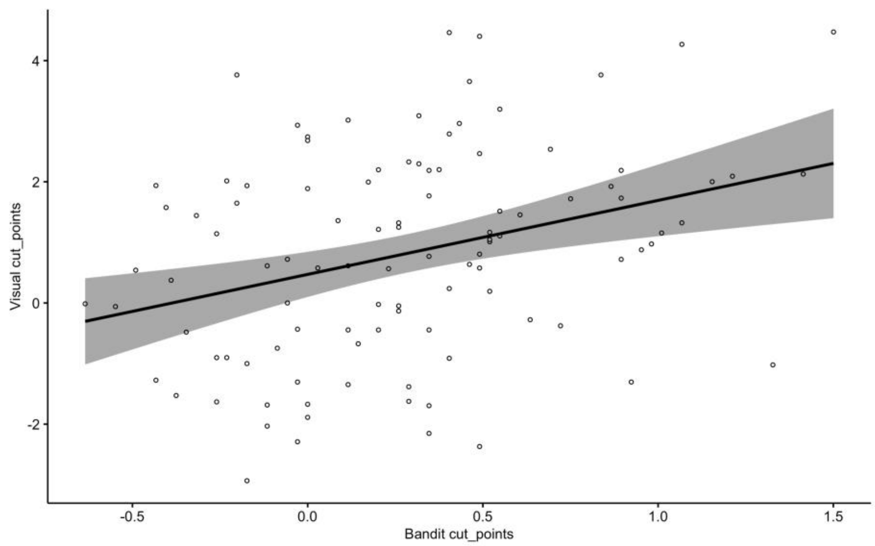
The best cutpoint was calculated for each subject and each period for both tasks. $cutpoint_{Bit}$ and $cutpoint_{Vit}$ hold these values for the bandit and visual task, respectively. t is the period $\in \{1,...,20\}$, and i identifies the participant. Each period involved 10 rounds. Similar to the mentioned analysis of the last part, the Abowd et al. (1999)[51] method was applied here as well.

The relation between both tasks' cutpoints were investigated after removing the effect of gender and risk preferences from each participants' data (Eq. 2).

$$cutpoint_{Bit} = \alpha \times gender_i + \beta \times risk_i + \gamma_{it} + \varepsilon \qquad (2)$$

Removing these covariates led the remaining part of the dependent variable to explain the main effect (γ_{it}). The scatter plot of Figure 2.6 shows the relation between these remaining variables in both bandit and visual tasks of all participants. As it is clear from this figure, there was a positive correlation between cutpoints in the two tasks, such that a unit increase in visual cutpoint increased bandit cutpoint by .33, $r(106) = .33$, $p < .001$.

Figure 2.6: Scatter plot of both tasks' cutpoints.



Notes: X-axis and Y-axis depict cutpoints in the bandit task and the visual task respectively. There is a significant moderate positive correlation between them.

From the results mentioned above, there is a strong relationship between the two tasks when the effect of gender and risk preferences was controlled and heterogeneity removed.

2.6 Conclusion

The purpose of this study is to investigate the consistency of people's exploratory behavior in two seemingly unrelated tasks. They are unrelated in appearance, but they measure a similar exploration-exploitation response in different contexts. The bandit task is designed to evaluate choice behavior, and the visual task, the innovation of this study, to assess searching behavior.

There is a strong positive relation between participants' exploration and a moderate positive relation between their cutpoints from the measurements related to these behaviors in both tasks. Exploration and cutpoint are higher in the visual task than in the bandit. Here, cutpoints can be considered another way to test the main hypothesis and could be viewed as a robustness check for the exploration.

Concluded from this study's result, there is a strong correlation between the two contexts, and thus exploratory behavior is consistent in choice and visual sampling. However, people tend to explore more in the visual task even though they cannot find the higher value, their expectation of finding it is higher. However, the experiment's design in the bandit task makes them more prone to stop exploration while seeing there is no chance to get higher values after three repeated choices of the exploratory arm. This can define a lower exploration rate in the bandit task. To give more freedom in choice similar to the visual task, the bandit task can change with an unknown number of the periods from the participants' point of view, similar to what Banks, Olson and Porter (1997) [8] did. Thus, they will not be able to guess the occurrence of the specific outcomes after several rounds.

These results are on the contrary with the Helversen et al.'s (2018) [7] findings as they didn't find a significant association between the exploration-exploitation behavior of people over three different exploration-exploitation tasks. As is mentioned, they did not take into account task-specific factors like task domain [19], order effect and horizon effects [21,22]; all factors that influence individual levels of exploration [7]. This could be the reason behind their findings.

The current study investigated younger adults' behavior only (average age of 24.5±4). Developmentally older individuals are more likely to use acquired skills, knowledge, and experiences, while younger individuals are more likely to take risks with something new. Thus, cues of older age groups can serve as an honest signal of one's ability to establish exploitation compared with the younger ages [52]. Thus, it is suggested for future work to study older adults' behavior as well, which, on the contrary to the result of this study, is expected to show more exploitative behavior. Such a perspective can give a good insight into the exploration-exploitation behavior from the developmental point of view.

References

1. Hills, T. T., Todd, P. M., Lazer, D., Redish, A. D., Couzin, I. D., & Cognitive Search Research Group. (2015). Exploration versus exploitation in space, mind, and society. *Trends in Cognitive Sciences*, *19*(1), 46–54.
2. Walker, A., Le Pelley, M., & Beesley, T. (2017). *Exploitative and Exploratory Attention in a Four-Armed Bandit Task.* CogSci.
3. Berger-Tal, O., Nathan, J., Meron, E., & Saltz, D. (2014). The exploration-exploitation dilemma: A multidisciplinary framework. *PloS One*, *9*(4), e95693.
4. Dennison, J. B., Sazhin, D., & Smith, D. V. (2020). *Decision Neuroscience and Neuroeconomics: Recent Progress and Ongoing Challenges*.
5. Addicott, M. A., Pearson, J. M., Sweitzer, M. M., Barack, D. L., & Platt, M. L. (2017). A primer on foraging and the explore/exploit trade-off for psychiatry research. *Neuropsychopharmacology*, *42*(10), 1931–1939.
6. Chakroun, K. (2019). *Dopaminergic modulation of the explore/exploit trade-off in human decision making*.
7. von Helversen, B., Mata, R., Samanez-Larkin, G. R., & Wilke, A. (2018). Foraging, exploration, or search? On the (lack of) convergent validity between three behavioral paradigms. *Evolutionary Behavioral Sciences*, *12*(3), 152.
8. Banks, J., Olson, M., & Porter, D. (1997). An experimental analysis of the bandit problem. *Economic Theory*, *10*(1), 55–77.
9. Gittins, J. (1974). A dynamic allocation index for the sequential design of experiments. *Progress in Statistics*, 241–266.
10. Payzan, É., & Bossaerts, P. (2009). *Decision-making under uncertainty in dynamic settings: An experimental study*.

11. Knox, W. B., Otto, A. R., Stone, P., & Love, B. (2012). The nature of belief-directed exploratory choice in human decision-making. *Frontiers in Psychology*, *2*, 398.
12. Daw, N. D., O'doherty, J. P., Dayan, P., Seymour, B., & Dolan, R. J. (2006). Cortical substrates for exploratory decisions in humans. *Nature*, *441*(7095), 876–879.
13. Steyvers, M., Lee, M. D., & Wagenmakers, E.-J. (2009). A Bayesian analysis of human decision-making on bandit problems. *Journal of Mathematical Psychology*, *53*(3), 168–179.
14. Srivastava, V., Reverdy, P., & Leonard, N. E. (2013). *On optimal foraging and multi-armed bandits*. 494–499.
15. Moustafa, A. A., Cohen, M. X., Sherman, S. J., & Frank, M. J. (2008). A role for dopamine in temporal decision making and reward maximization in parkinsonism. *Journal of Neuroscience*, *28*(47), 12294–12304.
16. Billinger, S., Srikanth, K., Stieglitz, N., & Schumacher, T. R. (2021). Exploration and exploitation in complex search tasks: How feedback influences whether and where human agents search. *Strategic Management Journal*, *42*(2), 361–385.
17. Dall, S. R., Houston, A. I., & McNamara, J. M. (2004). The behavioural ecology of personality: Consistent individual differences from an adaptive perspective. *Ecology Letters*, *7*(8), 734–739.
18. Fleeson, W., & Jayawickreme, E. (2015). Whole trait theory. *Journal of Research in Personality*, *56*, 82–92.
19. Abebe, M. A., & Angriawan, A. (2014). Organizational and competitive influences of exploration and exploitation activities in small firms. *Journal of Business Research*, *67*(3), 339–345.
20. Blais, A.-R., & Weber, E. U. (2006). A domain-specific risk-taking (DOSPERT) scale for adult populations. *Judgment and Decision Making*, *1*(1).
21. Wilson, R. C., Geana, A., White, J. M., Ludvig, E. A., & Cohen, J. D. (2014). Humans use directed and random exploration to solve the explore–exploit dilemma. *Journal of Experimental Psychology: General*, *143*(6), 2074.
22. Averbeck, B. B. (2015). Theory of choice in bandit, information sampling and foraging tasks. *PLoS Computational Biology*, *11*(3), e1004164.

23. Eriksson, P. E. (2017). Procurement strategies for enhancing exploration and exploitation in construction projects. *Journal of Financial Management of Property and Construction*.
24. Blanco, M., Engelmann, D., Koch, A. K., & Normann, H.-T. (2010). Belief elicitation in experiments: Is there a hedging problem? *Experimental Economics*, *13*(4), 412–438.
25. Dezza, I. C., Angela, J. Y., Cleeremans, A., & Alexander, W. (2017). Learning the value of information and reward over time when solving exploration-exploitation problems. *Scientific Reports*, *7*(1), 1–13.
26. Bella-Fernández, M., Suñé, M. S., & de Liaño, B. G.-G. (2021). Foraging behavior in visual search: A review of theoretical and mathematical models in humans and animals. *Psychological Research*, 1–19.
27. Eckstein, M. P. (2011). Visual search: A retrospective. *Journal of Vision*, *11*(5), 14–14.
28. Fiedler, S., & Glöckner, A. (2012). The dynamics of decision making in risky choice: An eye-tracking analysis. *Frontiers in Psychology*, *3*, 335.
29. Orquin, J. L., & Loose, S. M. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica*, *144*(1), 190–206.
30. Stojić, H., Orquin, J. L., Dayan, P., Dolan, R. J., & Speekenbrink, M. (2020). Uncertainty in learning, choice, and visual fixation. *Proceedings of the National Academy of Sciences*, *117*(6), 3291–3300.
31. Brunyé, T. T., Drew, T., Weaver, D. L., & Elmore, J. G. (2019). A review of eye tracking for understanding and improving diagnostic interpretation. *Cognitive Research: Principles and Implications*, *4*(1), 1–16.
32. Ehinger, B. V., Kaufhold, L., & König, P. (2018). Probing the temporal dynamics of the exploration–exploitation dilemma of eye movements. *Journal of Vision*, *18*(3), 6–6.
33. Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & Van de Weijer, J. (2011). *Eye tracking: A comprehensive guide to methods and measures*. OUP Oxford.
34. Walker, A. R., Luque, D., Le Pelley, M. E., & Beesley, T. (2019). The role of uncertainty in attentional and choice exploration. *Psychonomic Bulletin & Review*, *26*(6), 1911–1916.

35. Beesley, T., Nguyen, K. P., Pearson, D., & Le Pelley, M. E. (2015). Uncertainty and predictiveness determine attention to cues during human associative learning. *Quarterly Journal of Experimental Psychology*, *68*(11), 2175–2199.

36. Gameiro, R. R., Kaspar, K., König, S. U., Nordholt, S., & König, P. (2017). Exploration and exploitation in natural viewing behavior. *Scientific Reports*, *7*(1), 1–23.

37. Wolfe, J. M. (2013). When is it time to move to the next raspberry bush? Foraging rules in human visual search. *Journal of Vision*, *13*(3), 10–10.

38. Kristjánsson, Á., Björnsson, A. S., & Kristjánsson, T. (2020). Foraging with Anne Treisman: Features versus conjunctions, patch leaving and memory for foraged locations. *Attention, Perception, & Psychophysics*, 1–14.

39. Callaway, F., Rangel, A., & Griffiths, T. L. (2021). Fixation patterns in simple choice reflect optimal information sampling. *PLoS Computational Biology*, *17*(3), e1008863.

40. Anderson, B. A. (2016). The attention habit: How reward learning shapes attentional selection. *Annals of the New York Academy of Sciences*, *1369*(1), 24–39.

41. Failing, M., & Theeuwes, J. (2018). Selection history: How reward modulates selectivity of visual attention. *Psychonomic Bulletin & Review*, *25*(2), 514–538.

42. Gluth, S., Spektor, M. S., & Rieskamp, J. (2018). Value-based attentional capture affects multi-alternative decision making. *Elife*, *7*, e39659.

43. Manso, G. (2017). Creating incentives for innovation. *California Management Review*, *60*(1), 18–32.

44. Rim, N. W., Choe, K. W., Scrivner, C., & Berman, M. G. (2021). Introducing Point-of-Interest as an alternative to Area-of-Interest for fixation duration analysis. *Plos One*, *16*(5), e0250170.

45. Perkovic, S., Schoemann, M., Lagerkvist, C. J., & Orquin, J. L. (2021). *Covert attention leads to fast and accurate decision making*.

46. SR Research. (2009). *EyeLink 1000 User Manual*.

47. Orquin, J. L., Ashby, N. J., & Clarke, A. D. (2016). Areas of interest as a signal detection problem in behavioral eye-tracking research. *Journal of Behavioral Decision Making*, *29*(2–3), 103–115.

48. Brosig, J., Reichmann, T., & Weimann, J. (2007). Selfish in the end? An investigation of consistency and stability of individual behaviour. *Working Paper Series*.

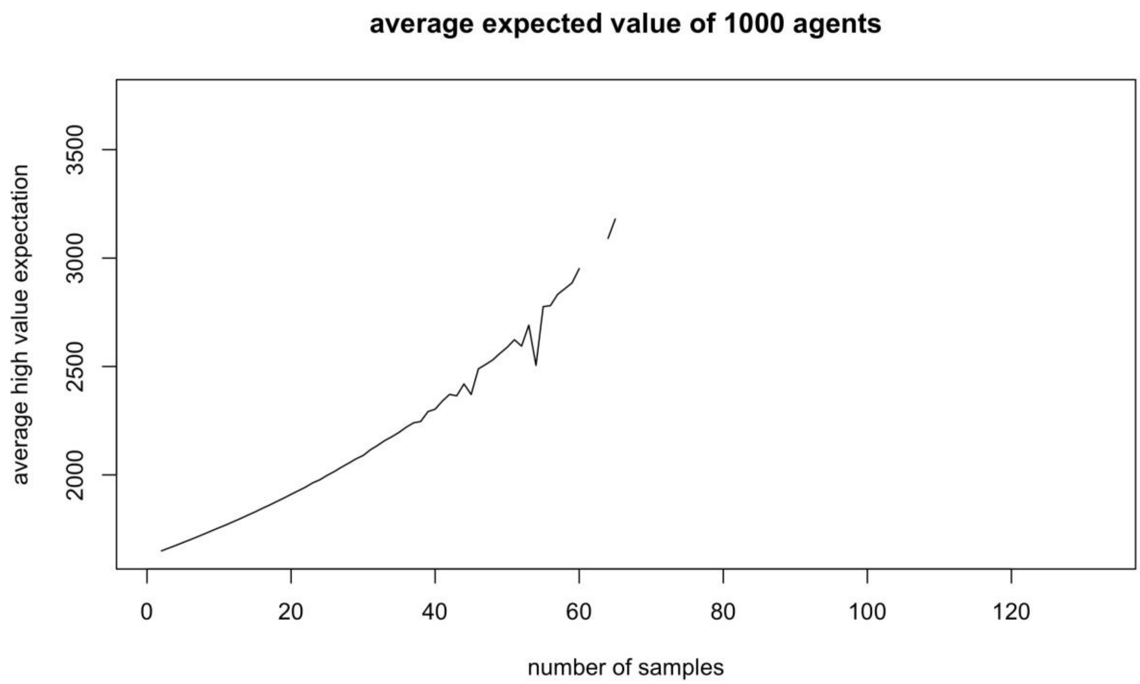
49. Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, *9*(3), 522–550.
50. Kim, J., & Shin, W. (2014). How to do random allocation (randomization). *Clinics in Orthopedic Surgery*, *6*(1), 103–109.
51. Abowd, J. M., Kramarz, F., & Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, *67*(2), 251–333.
52. Spisak, B. R., Grabo, A. E., Arvey, R. D., & Van Vugt, M. (2014). The age of exploration and exploitation: Younger-looking leaders endorsed for change and older-looking leaders endorsed for stability. *The Leadership Quarterly*, *25*(5), 805–816.
53. White, H. (2017). *Beginning Computer Science with R*.

2.7 Appendix

2.7.1 Monte Carlo simulation

Monte Carlo is a simulation method to solve problems with probabilistic interpretation[53]. The main idea is based on sampling repeatedly and randomly to solve complex problems by other approaches. The first step was to produce values needed to put on the task's screen (132 random values from two higher and lower ranges). Then to simulate actual selection behavior many times, Monte Carlo simulation came into play. It was defined to sample randomly from 132 generated values. To simulate a sense of sampling from different numbers, a field value was set to change from 1 to 132. 1 means looking at only one value, 2 means two values, and 132 means searching all the values. These were simulated by sampling these fields 1000 times from our task space values. The expected value of each field was approximated by averaging over their simulated values. The expectation of finding the highest value was calculated by counting the occurrence of the task space's highest value divided by the number of sampling (probability) times the highest value. This expectation is also calculated over fields which are shown in Figure 2.7. This indicates that an increase in the number of search fields increases the probability of finding the largest value.

Figure 2.7: Expected payoffs.

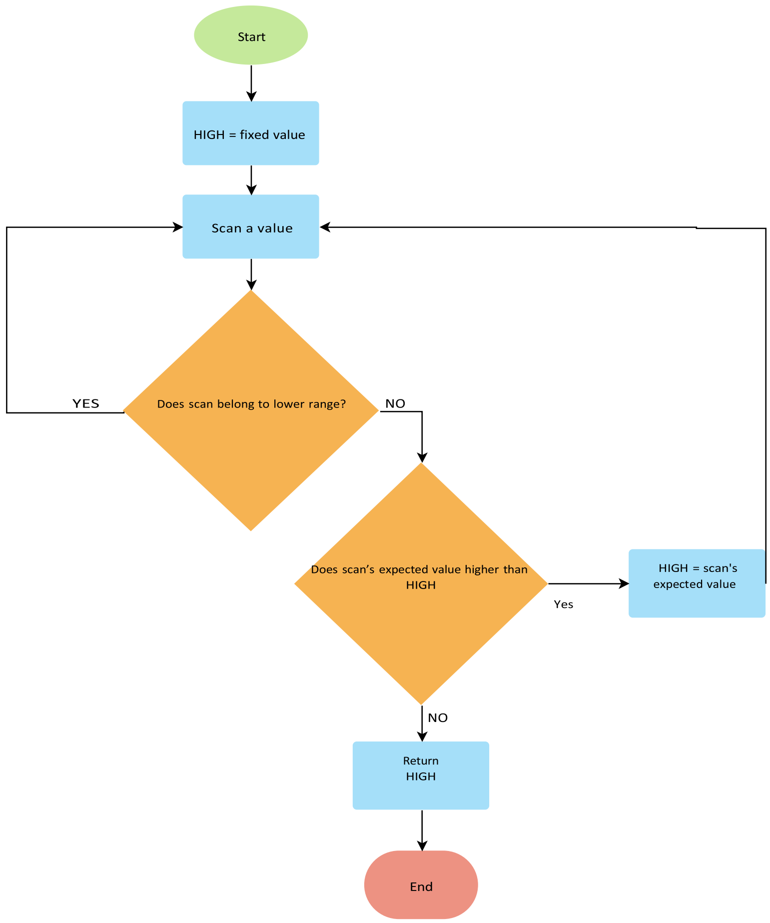


Notes: Expected payoffs are shown for searching through 1 to 132 options. The horizontal axis shows the number of fields and the vertical axis is the approximation of the expected value of searching in every fields 1000 times.

The flowchart of this process for a risk-neutral decision maker using a myopic strategy can be found in Figure 2.8). It starts by choosing fixed value as the highest value. It continues by searching options one by one to find one with a higher expected value than the previous one. By getting a draw from the lower interval, searching will continue. If the found value's expected value is higher than the previous one, the highest value is updated to the new one. If the draw does not belong to the upper bound, the highest value remains unchanged. In both mentioned conditions, searching continues. However, when the value is chosen from the upper bound and is not higher than the previous highest value, searching is terminated. After each draw, one decreases from the number of related low/high intervals and overall numbers. The expected value of finding a high value is calculated by the number of higher options divided by the total number of values.

By simulating this process 1000 times and considering the time limit of a period, the average sampling number to find the highest value with a time limit equal to one period (15 seconds) is 10.6±8.4 values. However, this value by the time limit before the center option's first reduction (3 seconds) is 7.16 ± 2.9.

Figure 2.8: Flowchart of risk neutral sampling.



2.7.2 Instructions and consent form

These are instruction forms which were used in this study for both counterbalance groups.

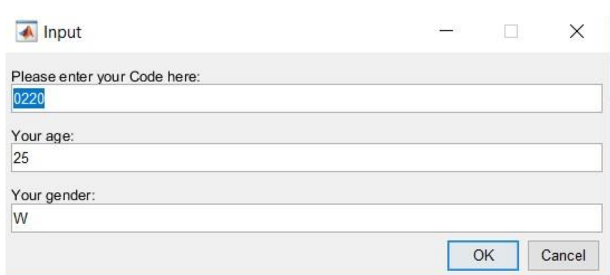
Instructions for the choice task study1:

You are about to participate in an individual decision-making experiment. The decisions you will make during the experiment will result in earnings that will be paid to your bank account in about 2-6 weeks. Please follow the instructions carefully to understand how you can accumulate earnings. The experiment will be broken up into two parts. There will be a calibration phase before each part and a short break between the parts. After both parts are completed, your payment will be computed. You will receive instructions for each part separately. All values will be stated in terms of tokens. Tokens will be converted to DKK at a rate of 1 DKK= 3380 tokens. Your payment will be the converted amount rounded up to full kroner amount plus a 45 DKK fixed compensation. Depending on the number of tokens you earn, your payment is in the range starting from 45 DKK for zero tokens to 145 DKK for the highest amount of earned tokens. Please take your time to carefully think about your decision.

Calibration

Because we are investigating dynamic decision-making, we need to track your eye movements using an eye tracker. The device can only detect your eyes' position when your head moves as little as possible. Using a head stabilizer helps us get better data and also protects you from the fatigue of keeping your head steady for a long time. In the beginning, we will find a convenient position for you to sit in front of the computer and place your head on the stabilizer.

Before the calibration, you must enter your identification code, age, and gender (see example below).



During calibration you will be asked to focus on a black dot on the screen. This is necessary to calibrate the eye-tracker for your eyes to get reliable data. Simply look at the dot and follow it anywhere it goes. It is very important that you follow the dot carefully. The calibration takes less than three minutes.

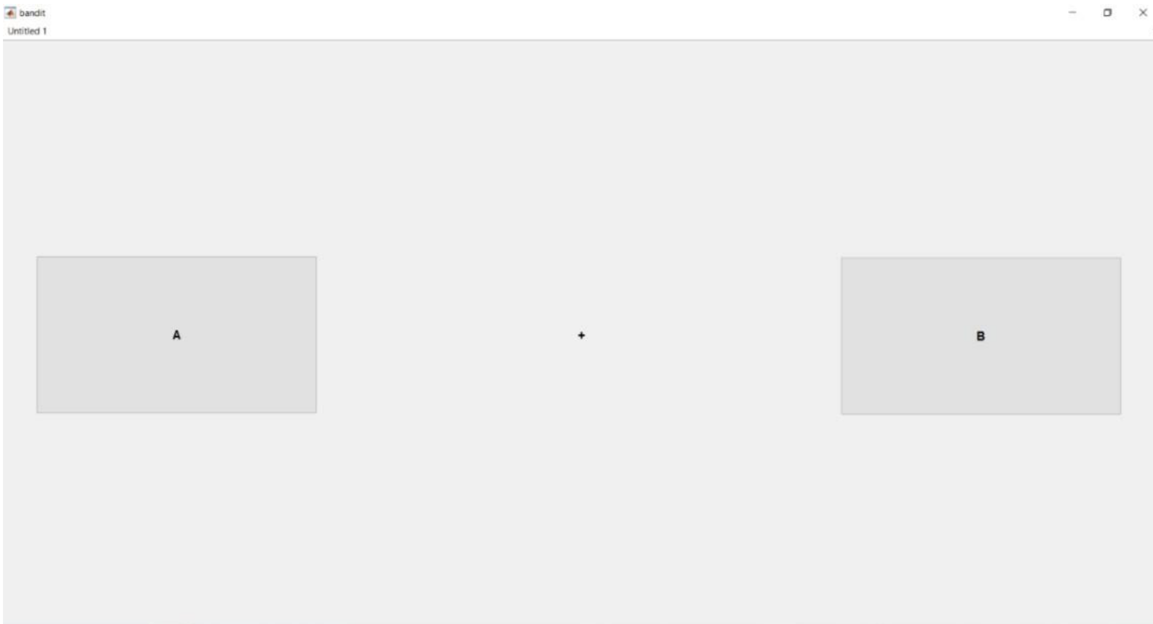
Part 1 – Task 1

This part of the experiment will be broken up into 20 periods. Each period in turn will be divided into 10 rounds in which you will make decisions and earn profits. At the beginning of a round, you will make a choice between two alternatives called A and B.

- The A alternative will pay you 845 tokens if you select it as it is shown in picture below.
- The B alternative will be one of two possible types which we will call good and bad.
  - If B is good, you will receive 1690 tokens with a 90 percent chance and 0 tokens with a 10 percent chance.
  - If B is bad, then your chance of obtaining 1690 tokens will be lower and the chance of obtaining 0 tokens will be higher. Specifically, it pays 1690 tokens with a 10 percent chance and 0 tokens with a 90 percent chance.

After you select either alternative A or B you will be informed of your payoff for the round.

Option B has the same type, good or bad, over all rounds in a period. In round 1, of each period of this experiment, the A alternative pays 845 tokens if you select it as it is shown in picture below. The B alternative could be a good type that pays 1690 tokens with a 90 percent chance and 0 tokens with a 10 percent chance. This means, if B is good, then over many rounds you could expect to earn, on average 1521 tokens a round. On the other hand, B could be a bad type which pays 1690 tokens with a 10 percent chance and 0 tokens with a 90 percent chance. This means if B is bad, then over many rounds you could expect to earn, on average, 169 tokens a round. After 10 rounds, the new period starts with a new draw for the type of option B. Your final score for this task is the sum of your profits over all of your choices. After completion of this task you will rest for 3 minutes.



We now summarize the specific features of this experiment:

1. Alternative A pays 845 tokens.
2. At the beginning of a period, the B alternative will be selected as either a good type or a bad type with a fixed chance. It will remain that type for the entire period.
3. The chance that B is good is 50 percent.
4. If B is good it will pay 1690 tokens with a 90 percent chance and 0 tokens with a 10 percent chance in the first iteration of each period.
5. If B is bad it will pay 1690 tokens with a 10 percent chance and 0 tokens with a 90 percent chance.

Questions

Please answer to these questions and return this paper to the researcher after you finished.

1- What is the highest value you can earn from choosing option A?

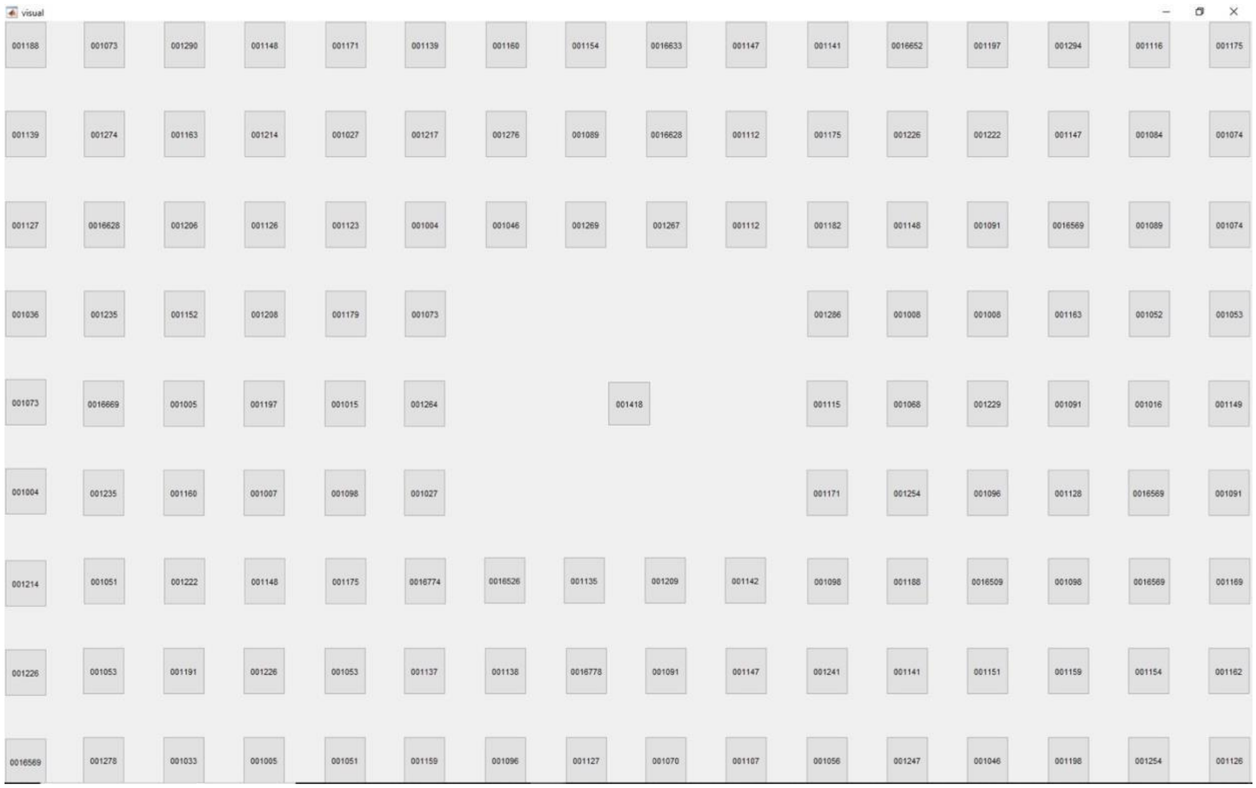
2- What is the lowest value you can earn from choosing option A?

3- What is the highest value you can earn from choosing option B?

4- What is the lowest value you can earn from choosing option B?

Part 2– Task 2

In this part of study, you will enter the task 2 and start choosing your desired option for 20 periods and earn profits. In each period, you will make a choice between 133 alternatives with different tokens (see example screenshot below). There will be two kinds of options there. One center option and 132 surrounding options. The center option will pay you a number of tokens in the range 1350, 1351, …, 1649, 1650, where each number has the same probability of being selected. From the 132 surrounding options, 13 of them will pay more tokens than the center option and 119 of them will pay fewer tokens than the center option. The 13 higher values will be drawn from the range 16600, 16601,…,16900 and the 119 lower values will be drawn from the range 1000, 1001,..1300. Again, all numbers in the respective ranges have the same probability of being drawn. An example screenshot of this task is shown below.



The number of tokens awarded for the centered option will decrease by 10 points every 3 seconds and you will have a total of 15 seconds for choosing an option. If you do not make a choice within 15 seconds the system will choose 0 points for you and go to the next period. Each period starts with a new draw of the values for all the options. Your final score for this task is the sum of your gains over all of these 20 periods.

We now summarize the specific features of this experiment:

1. The centre option pays a number of tokens in the range 1350 to 1650.
2. The surrounding options will pay either fewer or more tokens than the centre option
    - 13 options will pay tokens in the range 16600–16900.
    - 119 options will pay tokens in the range 1000–1300.
3. The token value of the center option will decrease by 10 points every 3 seconds.

4. You have 15 seconds to choose an option. Otherwise 0 tokens will be chosen as the score of that period.
5. You play 20 periods.

Questions

1- What is the range of the 119 lower valued options?

2- What is the range of the 13 higher valued options?

3- What is the range of the fixed option?

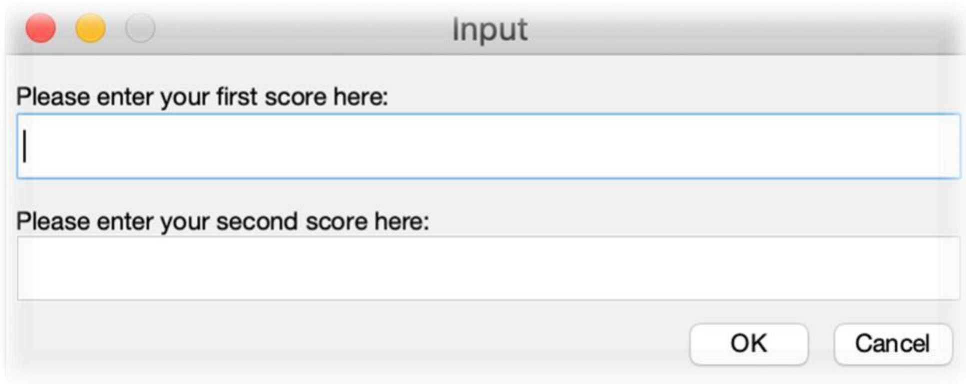
4- Put the appropriate symbol for this sentence in the boxes below (< = >)

Lower range numbers ☐ Fixed option ☐ Higher range numbers

Payment

In this part, one of your tasks' scores will be drawn randomly. As it is shown below, in this step researcher will write both of your scores in their relevant section and wait for the computer to select one of them randomly and calculate the payment for you. In the worst-case scenario with the lowest number of tokens which is 0, you would receive 45 kroner while in the best case you will earn 145 kroner.

Please write your final score on your bank transfer receipt and sign it.



While participating in the experiment please:

- Take your time to carefully think about your decision.
- Click on your choice once and wait for your mouse pointer to be placed in the center of the screen before making your next choice.
- Remember that your objective is to gather as many points as you can because your payment will be based on that.

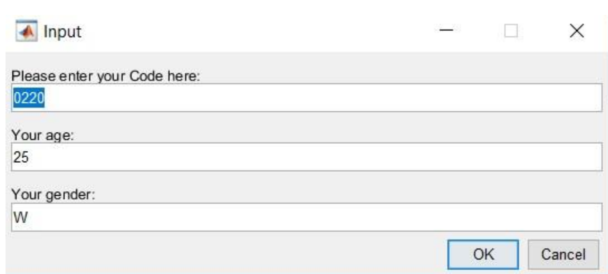
Instructions for the choice task study2

You are about to participate in an individual decision-making experiment. The decisions you will make during the experiment will result in earnings that will be paid to your bank account in about 2-6 weeks. Please follow the instructions carefully to understand how you can accumulate earnings. The experiment will be broken up into two parts. There will be a calibration phase before each part and a short break between the parts. After both parts are completed, your payment will be computed. You will receive instructions for each part separately. All values will be stated in terms of tokens. Tokens will be converted to DKK at a rate of 1 DKK= 3380 tokens. Your payment will be the converted amount rounded up to full kroner amount plus a 45 DKK fixed compensation. Depending on the number of tokens you earn, your payment is in the range starting from 45 DKK for zero tokens to 145 DKK for the highest amount of earned tokens. Please take your time to carefully think about your decision.

Calibration

Because we are investigating dynamic decision-making, we need to track your eye movements using an eye tracker. The device can only detect your eyes' position when your head moves as little as possible. Using a head stabilizer helps us get better data and also protects you from the fatigue of keeping your head steady for a long time. In the beginning, we will find a convenient position for you to sit in front of the computer and place your head on the stabilizer.

Before the calibration, you must enter your identification code, age, and gender (see example below).



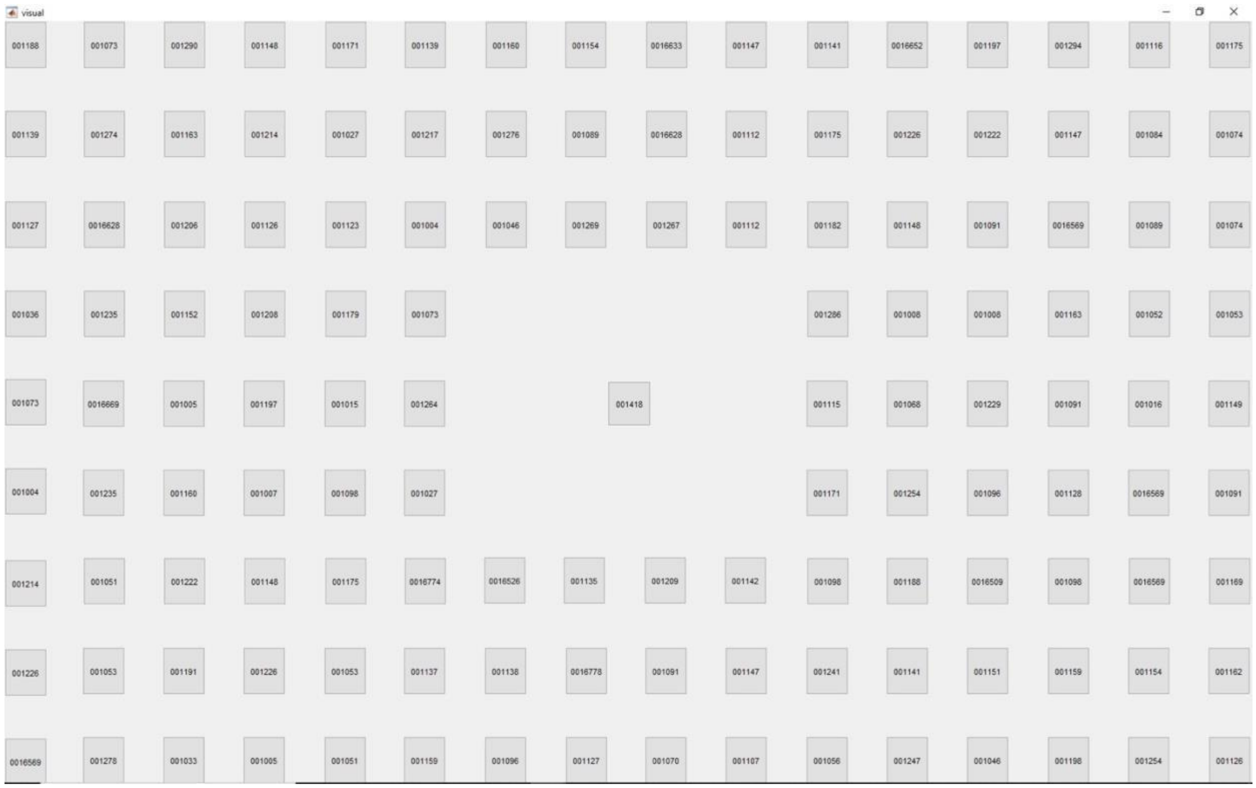
During calibration you will be asked to focus on a black dot on the screen. This is necessary to calibrate the eye-tracker for your eyes to get reliable data. Simply look at the dot and follow it anywhere it goes. It is very important that you follow the dot carefully. The calibration takes less than three minutes.

Part 1 – Task 1

In this part of study, you will enter the task 1 and start choosing your desired option for 20 periods and earn profits. In each period, you will make a choice between 133 alternatives with different tokens (see example screenshot below). There will be two kinds of options there. One center option and 132 surrounding options. The center option will pay you a number of tokens in the range 1350,

1351, …, 1649, 1650, where each number has the same probability of being selected. From the 132 surrounding options, 13 of them will pay more tokens than the center option and 119 of them will pay fewer tokens than the center option. The 13 higher values will be drawn from the range 16600, 16601,…,16900 and the 119 lower values will be drawn from the range 1000, 1001,..1300.

Again, all numbers in the respective ranges have the same probability of being drawn. An example screenshot of this task is shown below.



The number of tokens awarded for the centered option will decrease by 10 points every 3 seconds and you will have a total of 15 seconds for choosing an option. If you do not make a choice within 15 seconds the system will choose 0 points for you and go to the next period. Each period starts with a new draw of the values for all the options. Your final score for this task is the sum of your gains over all of these 20 periods. After completion of this task you will rest for 3 minutes.

We now summarize the specific features of this experiment:

1. The centre option pays a number of tokens in the range 1350 to 1650.
2. The surrounding options will pay either fewer or more tokens than the centre option
    a. 13 options will pay tokens in the range 16600–16900.
    b. 119 options will pay tokens in the range 1000–1300.
3. The token value of the center option will decrease by 10 points every 3 seconds.

4. You have 15 seconds to choose an option. Otherwise 0 tokens will be chosen as the score of that period.
5. You play 20 periods.

Questions

1- What is the range of the 119 lower valued options?

2- What is the range of the 13 higher valued options?

3- What is the range of the fixed option?

4- Put the appropriate symbol for this sentence in the boxes below (< = >)

Lower range numbers □ Fixed option □ Higher range numbers

Part 2– Task 2

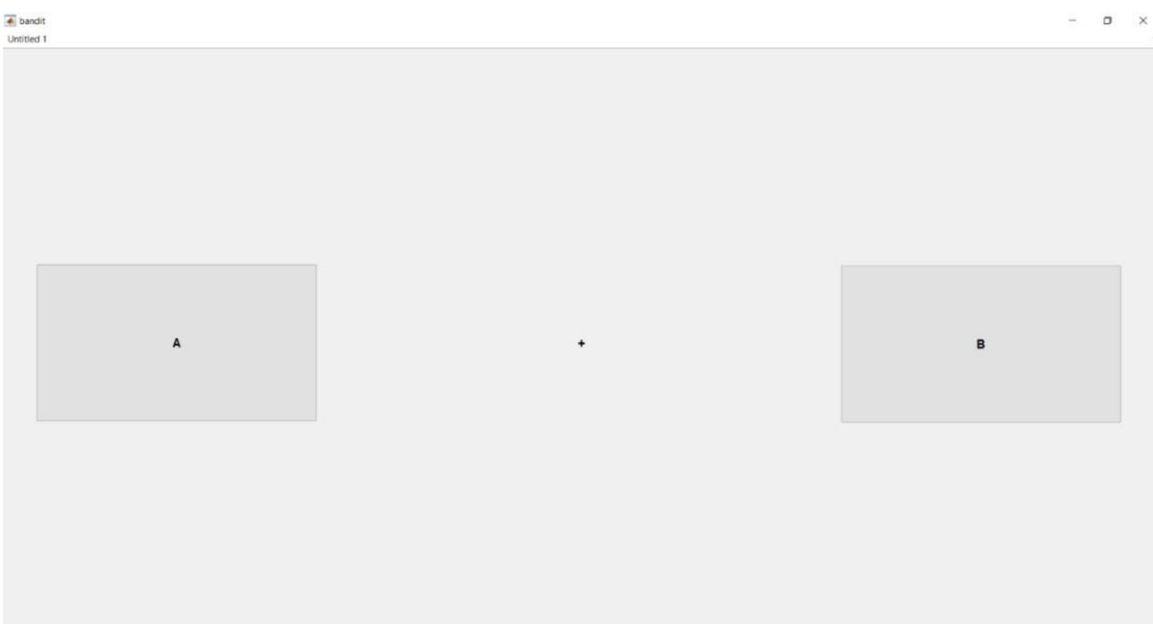
This part of the experiment will be broken up into 20 periods. Each period in turn will be divided into 10 rounds in which you will make decisions and earn profits. At the beginning of a round, you will make a choice between two alternatives called A and B.

- The A alternative will pay you 845 tokens if you select it as it is shown in picture below.
- The B alternative will be one of two possible types which we will call good and bad.
    - If B is good, you will receive 1690 tokens with a 90 percent chance and 0 tokens with a 10 percent chance.

- If B is bad, then your chance of obtaining 1690 tokens will be lower and the chance of obtaining 0 tokens will be higher. Specifically, it pays 1690 tokens with a 10 percent chance and 0 tokens with a 90 percent chance.

After you select either alternative A or B you will be informed of your payoff for the round.

Option B has the same type, good or bad, over all rounds in a period. In round 1, of each period of this experiment, the A alternative pays 845 tokens if you select it as it is shown in picture below. The B alternative could be a good type that pays 1690 tokens with a 90 percent chance and 0 tokens with a 10 percent chance. This means, if B is good, then over many rounds you could expect to earn, on average 1521 tokens a round. On the other hand, B could be a bad type which pays 1690 tokens with a 10 percent chance and 0 tokens with a 90 percent chance. This means if B is bad, then over many rounds you could expect to earn, on average, 169 tokens a round. After 10 rounds, the new period starts with a new draw for the type of option B. Your final score for this task is the sum of your profits over all of your choices.



We now summarize the specific features of this experiment:

1. Alternative A pays 845 tokens.
2. At the beginning of a period, the B alternative will be selected as either a good type or a bad type with a fixed chance. It will remain that type for the entire period.
3. The chance that B is good is 50 percent.
4. If B is good it will pay 1690 tokens with a 90 percent chance and 0 tokens with a 10 percent chance in the first iteration of each period.
5. If B is bad it will pay 1690 tokens with a 10 percent chance and 0 tokens with a 90 percent chance.

Questions

Please answer to these questions and return this paper to the researcher after you finished.

1- What is the highest value you can earn from choosing option A?

2- What is the lowest value you can earn from choosing option A?

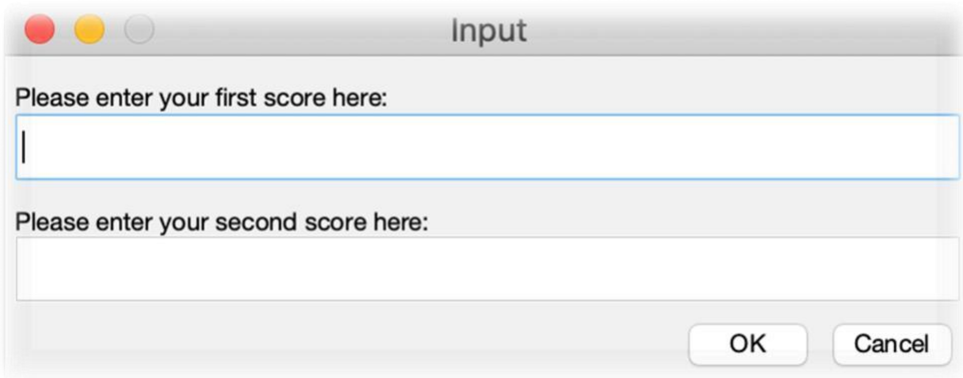
3- What is the highest value you can earn from choosing option B?

4- What is the lowest value you can earn from choosing option B?

Payment

In this part, one of your tasks' scores will be drawn randomly. As it is shown below, in this step researcher will write both of your scores in their relevant section and wait for the computer to select one of them randomly and calculate the payment for you. In the worst-case scenario with the lowest number of tokens which is 0, you would receive 45 kroner while in the best case you will earn 145 kroner.

Please write your final score on your bank transfer receipt and sign it.



While participating in the experiment please:

- Take your time to carefully think about your decision.
- Click on your choice once and wait for your mouse pointer to be placed in the center of the screen before making your next choice.
- Remember that your objective is to gather as many points as you can because your payment will be based on that.

Consent form

1. Title of research

You are invited to take part in the research study *Choice task* and we would like to ask you for your consent to participate in the study and for us to treat your data in agreement with data protection legislation. Before you decide to participate in this study, it is important that you understand why the research is being done and what it will involve. Please take the time to read the following information carefully and ask the researcher if there is anything that is not clear or if you need more information.

Project description and aim of the study

We aim to investigate decision making as a dynamic process. Thus, we record the actions you perform in this experiment. In this study, you complete two different types of tasks. For each task you complete several rounds. Your pay for the participation depends on your total score as explained below. Your goal is to earn as much as you can.

Data controller, research group and principal investigator

Principal investigator: Fatemeh ShahrabiFarahani, ash@econ.au.dk

Data controller: Fatemeh ShahrabiFarahani, ash@econ.au.dk

2. Study procedure

After reading and signing this form you will receive a bank transfer receipt. On it, we ask for your name, CPRnumber, and Sona-ID. This is also where you should write your final score when the experiment is over. This receipt will be used for payment purposes only and kept separately from the other parts immediately after the experiment.

As mentioned, you will perform two tasks. One of them is a task where you choose between two options and the other is a task where you choose between many options. Before starting each task, you will receive the instruction related to that task. Each task starts by asking for your identification code, gender, and age. It is followed by a calibration stage where you are asked to track a black dot on the screen. Please note that we will need you to keep your head position fixed as much as possible during the experiment. When calibration is finished the first task starts. When it is finished you have 3 minutes to rest. Afterward, the procedure of receiving instructions, entering information, and calibration repeats before the second task starts. Your final payment will be a fixed compensation of 45 DKK in addition to a variable compensation calculated based on the total score in one of the two tasks. Which of the two tasks is relevant for payment is randomly selected by the computer at the end of the session. For that reason, you should carefully consider your choices in each task, as it may turn out to be the one that matters for your payment. Your goal is to earn as much as you can.

3. Benefits and risks

The experiment involves no risks beyond those encountered in normal everyday life. You will receive between 45 to 145 DKK based on your scores by participating in the experiment. The study is expected to last 35-45 minutes depending on your pace.

4. Type of personal data and when it is deleted/anonymized

We process normal personal information in form of your CPR-number to make payments for participation in the study.

Your personal data (CPR-numbers and Names) will not be saved anywhere else than in your payment slip. They will be shredded as soon as payments are finalized, which will be about two months after the study has taken place.

When you signed up for the study we had emailed you an identification code to link what you will do in different sections of the experiment in an anonymous manner. These emails will be deleted after finishing data collection. Since then, data will be anonymous.

5. Withdrawal of consent

Participation is voluntary and you may withdraw your consent at any time. This is done by contacting the data controller or the researcher during the study.

Signature

I confirm to have received, read and understood the above information and that:

A. My participation is voluntary, and I may withdraw my consent and discontinue participation in the project at any time as specified in point 5. My refusal to participate will not result in any penalty.

B. By signing this agreement, I do not waive any legal rights or release Aarhus University, its agents, or you from liability for negligence.

C. I give my consent to statistical analysis of my personal data and to my participation as a subject in the study as described above.

____

(Signature and date)

____

(Name of participant, please complete in block capitals)

CHAPTER **3**

The Dynamics of Decision-making in an Exploration-Exploitation Paradigm

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Abstract

Looking into eye and hand movements can illustrate behavioral patterns. Eyes depict attention and information gathering process, while hands show certainty and action in the decision process. We were interested in these two processes to find how they affect each other and how they are related in a bandit task: a two-choice gambling task making a tradeoff between choosing a known resource 'Exploit' vs. an unknown one 'Explore'.

Here certainty was measured using the time taken to make a choice. In addition, the relation between eye and hand coordinates was investigated using the cross-recurrence quantification method as both had non-linear characteristics. Results showed that while participants engaged in the exploitation, they had higher certainty about the outcome; thus, their eye-hand movements had a higher cross-recurrence rate. On the other hand, a lower cross-recurrence rate was detected in exploration in which certainty was lower about the outcome.

Keywords: Dynamic decision-making, CRQA, Eye-tracking, mouse-tracking, Exploration-Exploitation, Bandit

3.1 Introduction

Researchers in various disciplines have intensively studied decision-making, and there are several professional societies and journals dedicated to studying it. Exploration-exploitation is an important subject in decision-making studies, as adapting to a changing environment requires a fine balance between exploring novel knowledge domains or exploiting existing ones [1,2]. Exploration defines by discovering, experimenting with new unknown information, while exploitation is associated with relying on and using the existing knowledge [3,4].

Exploration-exploitation is a continuous decision process [1,5] regarding the consistent tradeoff between the two ends of a continuum. This process consists of a learning process that is enhanced during the time [6] such that in the case of exploration, returns are more distant in time; however, in contrast, in the case of exploitation, the returns are more achievable in a shorter timeframe. Temporal investigation of this process can shed light on the behavioral patterns, which evolve in time.
For decades, decision-making studies have only relied on the final choices and outcomes like errors and reaction times to interpret human behavior. However, such behavioral outcomes provide relatively little information about how cognitive processing evolves over time and how multiple processes may temporally converge to drive ultimate responses [7,8]. To have an insight into the underlying process leading to a choice and a better explanation of the behavior, process tracing methods were included in the studies [1,7–11].
Process-related approaches mainly used motor movements and brain activities [1,9–11]. As examples of brain studies, Laureiro-Martinez et al.[1] used an fMRI technique while participants engaged in a four-armed bandit.

This kind of tasks category is broadly used to study dynamics of exploration-exploitation behavior [1,12–14]. The basis of these tasks' category is a tradeoff between choosing one action over several sets of possibilities with different odds and rewards [1,12–14]. Relating to the research question, the number of these possible options can change. There are two, three, four, or even more possible options to choose from in the literature of the bandit task. These options are named 'arms' taken from gambling. In the beginning, participants have no idea about the arms payout; while arms differ in their odds and rewards, learning can happen after sampling from them.

Here, in each period, to maximize their total reward, participants had to resolve whether to choose a familiar arm (exploitation) or investigate a new one hoping for a higher payoff (exploration).

The study by Laureiro-Martinez et al. contained four arms that paid off points around four different means that changed from trial to trial. Although participants did not know about the changing means, they can learn about them by active sampling. In each trial they face a dilemma of choosing a familiar option or pursuing a new one [1].

Laureiro-Martinez et al. labeled choosing the same arm as in the previous trial as exploitation and choosing a different one as exploration. They showed that exploitation activates brain regions associated with reward seeking of the current choice. While exploration relies on brain regions associated with attentional control and tracking other choices' value (inhibition of the current choice to search for an alternative choice) [1].

In another study, pupil diameter was measured as an indicator of control state. It showed that exploratory choices resulted in larger pupil diameter than exploitative choices [15] (meaning of control is similar to the above-mentioned study).

As mentioned, motor activities can be viewed as the reflection of decision-making processes [11]. Researchers in the field have mainly focused on using movement tracking technologies [16,17]. Eye and mouse tracking are among the main continuous tracking systems used to trace cognitive processes' behavioral indicators. Eye tracking is widely used to distinguish attention, thinking, searching strategy, and information collection in visual tasks [18–20]. These cognitive abilities are inferred from information extracted from eye movement patterns, including fixation, saccade, scanpath, and gaze-related metrics. Such patterns have been used in a variety of applications including diagnosis of schizophrenia and Parkinson diseases [21,22] and also in tracing level of attention, memory, and emotion [22–25].

As an example, Choi et al. used eye-tracking in the exploration-exploitation study to measure creativity in the processing of web information of smartphone products. He defined participants' creativity by visual attention during exploration [26]. Visual attention was measured using metrics of total fixation duration, fixation count, and the number of times participants' gaze enters the AOI [26]. They divided the screen into three AOIs: reference, task activity, and alternatives. The reference AOI consists of smartphone specifications that can be used as a hint. Visual attention in the reference AOI was labeled as an exploitative activity, and the remaining AOIs labeled as exploratory. Results showed that task difficulty was consistent with more exploitative visual activity while time constraint had the opposite effect.

Similarly, mouse tracking also allows continuous detection of behavior which can be used to infer mental processes [18]. The behavioral response patterns can be classified by analyzing the path curves and speed of the hand movements. This information can be calculated from response times, changes in the x/y directions, sample entropy, or deviation from the ideal direct path [27–30].

In a mouse-tracking study, Dshemuchadse et al.[31] designed a binary choice task that participants had to choose between two options (sooner/smaller vs. later/larger) to investigate temporal discounting. The mouse cursor trajectory of the participants was recorded. A less direct mouse movement was seen when participants chose the option with later/larger rewards. This indicates participants need to overcome the attraction of the other option.

Decisions are executed by the motor system from their first to last steps as a process of comparing two or more choices to select between them [18,27,32]. Since the cognitive processes rely on collecting enough information before reaching a decision-making threshold, simultaneous use of eye-tracking and mouse tracking systems can help us to understand better the dynamics of the decision-making process [18]. In previous studies, researchers have shown that visual attention to the presented choices could predict the mouse responses [11,33]. For instance, mouse cursor movements have been used to illuminate pathologists' viewing strategies instead of the eye movements [33]. The spatial coupling between eye gaze and mouse cursor positions and a medium correlation between the overall mouse and eye movements have been reported [33]. Such a pattern has been confirmed by Koop and Johnson [11] by using a simple cumulative model. They showed that the x-coordination of the hand movements could be predicted from eye movements towards the instant preference option in a two-option preferential task. This indicates that eye movements have a bias toward the final choice in the decision-making process.

Furtner and Sachse [34] analyzed eye-hand coordination of 141 participants regarding eye guidance, eye-hand synchronicity, and hand guidance in three different complex labyrinths. Here, eye guidance was defined by the eye's view that supports hand movements' planning, while hand guidance accounted for this the other way around, and synchronization referred to the times that the eye and the hand were accurately at the same point. The results of the experimental investigation showed clear evidence in favor of eye guidance. In the other studies Pelz, Hayhoe, and Loeber [35] using a block-copying task, explore the temporal coordination of eye, head, and hand movements. Fixation was made to gather information about the blocking pattern, also guiding the hand visually to pick up and place blocks. Results showed that hand movements were delayed until the eye was ready for guiding the movement, and Sailer, Eggert, and Straube [36] showed a particularly early spatial separation between eye and hand. Thus, the eye rapidly takes up a new goal representation, while the hand still acts based on earlier information on the old target. Eye-hand coordination shows clear evidence in favor of eye guidance. According to Binsted et al.[37], the hand does not seem to be a slave of the eye. As they investigated, the hand remained exactly in a goal position while the eye rested beneath or above the goal position. Inquiries by Crawford, Medendorp, and Marotta [38] have also confirmed this view since only the hand movements can affect the environment directly.

These two modalities are different from each other because of the type of data they deal with. Movements of the hand offer a continuous stream of output that can reveal ongoing decision-making dynamics, while eye movements offer a continuous stream of input as information accumulation and attention. Recording mouse movements allows for analysis of reaction times, trajectories (with maximum deviation measures), and areas under the curve calculation for comparisons between different conditions [7,18,39]. Using both eye tracking and mouse tracking in combination could reveal important information about the dynamics of decision-making. Despite using discrete behavioral outcomes such as reaction times and errors, which provide little information on evolving cognitive processes, these dynamics could be used to assess how multiple processes temporally interact and how they are linked. An example of these approaches is analyzing the level of co-occurrence of the eye and hand movements [7,8,40–42].

Most of these studies have been developed based on a sequential sampling approach which assumes that decisions are made by accumulating information until reaching a threshold of evidence [43]. These models accounted for humans' limited mental capacity and thus considered information accumulation and extracting gradually [43]. Thus, decision-making is defined as a result of a dynamic process to collect evidence and then select a choice option [30]. Although these approaches may provide meaningful information about the emergence of a preferred option, they are less capable of tracking changes in strategies during decision-making [44].

Eye and hand movements are initiated by anatomically separate regions in the brain, and depending on the need, these movements can be coupled and decoupled [19,45]. The process of choosing an option depends on the information provided by the visual system. Hence a coupling between action and attention can be expected [45]. One of the common methods for measuring coupling is a correlation. However, this method is susceptible to the linearity of the input data [44]. When data does not have these properties, non-linear methods like Recurrence Quantification Analysis can be used. This technique is used to investigate dynamics of a time series [44,46–50]. Recurrence is patterns that repeat over time and caused by movements returned to similar states periodically.

It can be used for linear and nonlinear systems in any ordered (time or spatial) series [51]. This is unlike other methods such as ANOVA, that needs data to be normally distributed and have independent observations, a correlation that needs data to be linearly related or Fourier transform that needs data to be stationary which means that the statistical properties of the data (mean, variance and autocorrelation) should not change over time [51,52].

This is the strength of this method that it makes no assumptions about the mathematical structure, stationarity, or even origin of the data (data can be nominal, ordinal, or interval-scale data) [53]. It is a flexible method to study non-linear data series [50,54]. This technique is a non-linear equivalent of auto-correlation. It reconstructs the dynamical system underlying a time series, maps its possible states, and quantifies the trajectory of the system through these states. This grants quantitative indices of how strongly patterned a system's behavior is, which kinds of patterns are repeated, and how complex/flexible the repetitions are [44,46–50]. This method provides a good testbed for quantifying synchronization, coupling, and coordination [53].

To use as examples of finding synchrony of movements using this method, Richardson and Dale [47] looked at the coupling between a speaker's and a listener's eye movements in a television show using cross-recurrence analysis, and this showed that eye movements of a listener were closely coupled with a speaker's eye movements at a delay of 2 seconds. Wallot et al.[48] measured hand movements and heart rates during building model cars. Their hand movements showed greater synchrony when they were constrained more by a particular building strategy.

The Cross-recurrence Quantification (CRQA) technique is a bivariate extension of RQA that measures how and the extent to which two streams of information interact and come to exhibit similar patterns in time [44,50,55]. CRQA quantifies the strength but also the form and complexity of the shared dynamics of two systems. As a novelty of this study, this technique was applied to exploration-exploitation to investigate the eye and hand dynamics when people were making exploratory and exploitative decisions.

3.1.1 Hypotheses

Based on what Sinha et al. wrote in their review, outcomes in exploitation are more certain than outcomes in exploration as exploration has an unknown outcome while exploitation has a known, familiar one [6]. Certainty about the outcome is the subjective belief, before feedback, that a decision is correct and is inversely correlated with decision time [56]. It means that decisions with lower certainty require higher times while more certain decisions obtain faster. However, we don't know much about the dynamics of behavior in these two conditions. Using eye-hand movements and CRQA method, we investigate how attention and action are related when exploring or exploiting.

Thus, in the bandit task, we measure the feature of certainty without directly asking people, using their choice time. Due to the effect of certainty on behavior, we expect to see a higher correlation/coupling between eye and hand movements in exploitation when it has a higher certainty than a lower certainty in exploration.

3.2 Method

3.2.1 Two-armed bandit task

This experiment was run using a two-armed bandit task [12] which is described in detail in 'Chapter 2 - Exploration-Exploitation Flow in Choice and Visual Sampling'.

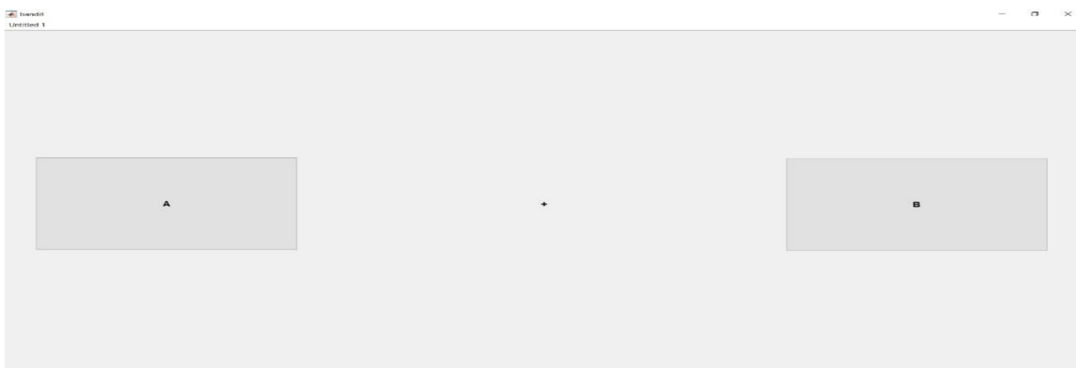
The Bandit task is a common test for examining exploration-exploitation.

The classical form of this task, known as the two-armed bandit, consists of the two options or 'arms' to choose from. One arm pays a certain outcome that does not change from round to round (fixed arm), while the other arm creates an uncertain outcome with some probability of paying twice a certain arm or nothing (varied arm)[12]. In the beginning participants did not have this information about the arms and must learn them by sampling from the arms. Current belief about the different arms determines optimal strategy in this task. In this regard, Gittins and Jones [9] introduced an index strategy. This strategy assigns a number to each arm depending on its outcome, and the arm with the higher index is nominated as the best decision. Based on this definition, if one started by selecting the fixed arm, she should stay there forever as no new information formed and the index does not change. On the other hand, if she started by choosing from the varied arm and a high outcome resulted, she should stay there as this result increases the index value for this arm [2,4,12].

There are several approaches to labeling arms as being exploratory or exploitative. For instance, in some studies, the option with the highest estimated value is classified as exploitatory, and selecting other options as exploratory [10–12]. Steyvers, Lee, and Wagenmakers [13] defined exploration as choosing an option with lesser successes and lesser failures than other choices and exploitation by choosing an alternative with higher successes and higher failures than another alternative.

Here, we used a similar two arms bandit task as Banks, Olson, and Porter [12] and labeled the fixed arm as exploitative behavior and varied arm as exploratory. Figure 3.1 shows a screenshot of this task.

Figure 3.1: Two-armed bandit



The left option (A) is the fixed option which always pays 845 points, and the right option (B) pays 1690 or 0 with some probabilities

Arm A offered a certain fixed outcome when it was selected (845 points), and arm B offered a good or bad outcome by the chance of 50%.

This experiment ran for 10 rounds and was repeated for 20 periods which means that each period contained 10 rounds. As the value under arm A is constant, the difference between periods showed itself in values under arm B. The value under arm B in each period could be good or bad with 50% chance and reset after 10 times of selection, regardless that choice was from arm A or B. Thus, from the 20 periods, 10 of them were good, and 10 of them were bad. There was a chance of 90% of winning 1690 points and 10% of winning nothing in a good period. Thus, from 10 rounds of each good period, almost 9 return 1690 while almost 1 return 0. While on the other hand, for the rounds belonging to the bad period, it is probable 10% of the time to win 1690 points and 90%

nothing (from 10 rounds, almost 9 of them return 0 while almost 1 of them return 1690). Used probabilities are identical to Banks, Olson, and Porter's [12] bandit task. This task is a part of another experiment that planned to make a comparison between them. Therefore, the reason behind choosing specific variables for the number of rounds, periods, and the value of the outcomes was to be congruent with the other task on that experiment. Please see 'Chapter 2 - Exploration-Exploitation Flow in Choice and Visual Sampling' experimental design section for more information.

3.2.2 Experimental sequence

All the participants received their identification code and a link to a questionnaire to rate their general risk-taking behavior after signing up for the study.

They received a consent form and instructions about the experiment when they came to the lab for the experiment. Then, as can be seen from Figure 3.2, they entered their identification code, age, and gender in a form shown on the screen.

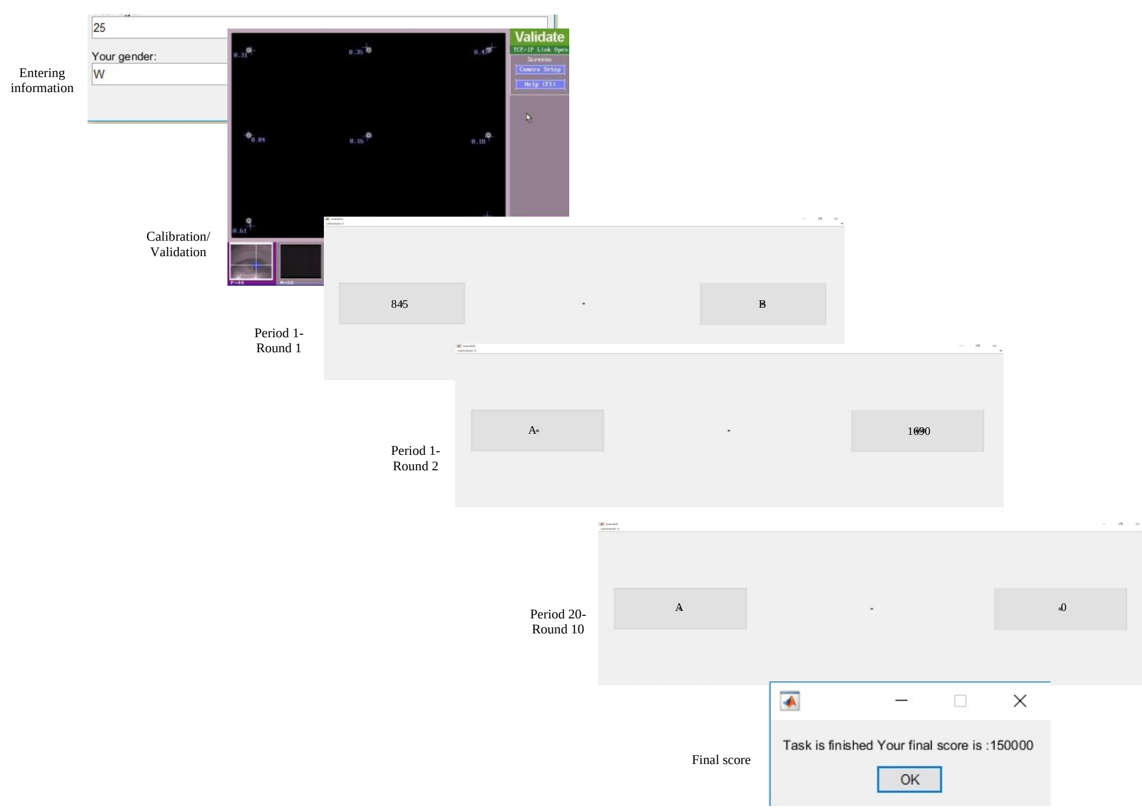
Eye movements were recorded by a desk-mounted EyeLink 1000 eye tracker with a monocular sampling rate of 1000 Hz [57,58]. Participants used a chin-rest to hold their head steady at approximately 60 cm viewing distance from the screen with a 1920 × 1080 pixels' resolution. The other initial parameters of the EyeLink remained unchanged.

After participants finished entering their information, a calibration procedure was performed. Calibration is the process to help customize and accurate gaze calculation using the geometric characteristics of the participant's eye and measures how the participant's eye reflects light. This was done by following a black dot on the screen using 13 points. In the case of having high accuracy, validation and drift check steps were then performed to make sure eye movement would be recorded adequately. After the successful calibration and validation (less than 1.0° of visual angle), the first period and its related first round was started, and participants had time until they made their choice by clicking on one of the A or B arms. As mentioned, there were 20 periods with the fixed outcome for arm A and probability-based outcome for arm B. Each period had 10 rounds. After each choice, the outcome behind the selected option was represented.

The outcome behind arm B was pre-randomized with two sequences to make variations. Half of the participants in each counterbalanced group received first, and the other half received the second sequence for this arm. After every 10 rounds, the value behind arm B was charged to the other pre-randomized value, which could be one of the good or bad types.

Each trial started by putting the mouse pointer over the cross shown at the center of the screen and between the two arms to make sure both mouse and eyes start their movements from the same initial position (half the width and length of the screen size). Here the starting point of the movement was the cross, and the ending point was either arm B or arm A depending on the decision. Specific starting and ending points gave more accurate data to compare. This horizontal placement of arms reduced dimension to only horizontal as the most prominent movements occurred in this dimension. After a total of 200 rounds, the outcome, which was the sum of the points earned over the whole 200

Figure 3.2 Experimental sequence



choices, was shown on the screen and recorded by the researcher. For example, the highest possible value could be 20×10×1690 = 338000 for the best-case scenario where all choices were from arm B, and all of them paid the highest outcome. The payment was the random selection between the outcome of the two tasks for the mentioned experiment in 'Chapter 2 - Exploration- Exploitation Flow in Choice and Visual Sampling'. The selected value was converted into Danish kroner (DKK) using an exchange rate of .0003 DKK/point plus a show-up fee of 45 DKK. The payment was 45 DKK in the worst-case scenario and 145 DKK in the best-case scenario.

3.2.3 Data collection and segmentation

As mentioned, EyeLink eye-tracker [57,58] was used to collect eye movements with the sampling frequency of 1 kHz. Hand movements were measured using mouse tracking with a sampling frequency of 250 Hz. GetMouse function from Psychophysics Toolbox Version 3 (PTB-3) was used here to return the position of the mouse cursor (x,y) [59].

The trackers have collected eye and hand coordinates repeatedly while the experiment was running. These coordinates were relative to the upper left corner as pixel (0,0). A message was sent to the eye-tracker as a marker to have a measurement for choice. Similarly, the time of making a choice was saved over the recording of the mouse data. By using the two sequential time series from each modality, it was possible to have segmented coordination for both eye and hand of each taken choice. Each segment of the eye-tracking data was then re-sampled by the factor of 1/4 to have the same sampling rate as the mouse does. The resample function in R from the signal library was used for this purpose using bandlimited interpolation [60].

There were 108 participants, each performing the bandit task for 200 trials and for each trial two series of eye and mouse movement coordinate were recorded. If the choice was from arm *A*, movements were labeled as exploitative, and when the choice was from arm *B*, they were assigned to exploratory movements. This data was recorded in two *x,y* dimensions. The only prominent dimension that we can expect more variability from was the horizontal axis due to the position of the arms in the experimental design. The arms were placed on a similar position in the vertical axis, while their *x* axes represented the variation between options. Thus, for further analysis, the horizontal axis was chosen for both eye and hand movement coordinates.

3.2.4 Participants

Participants were recruited from the subject pool of the Cognition and Behavior Lab at Aarhus University. A total of 122 subjects participated in the study. Half of them were doing the bandit task with the first sequence behind arm B, and the others faced the second sequence of data. Out of all participants, 14 subjects were excluded from the analysis because of a problem in the data collection (the experiment counted the number of clicks on each selected option; if they clicked several times on one option repeatedly except one time, it was counted and finished the program earlier than expected. The ones who clicked more than what was expected were excluded).

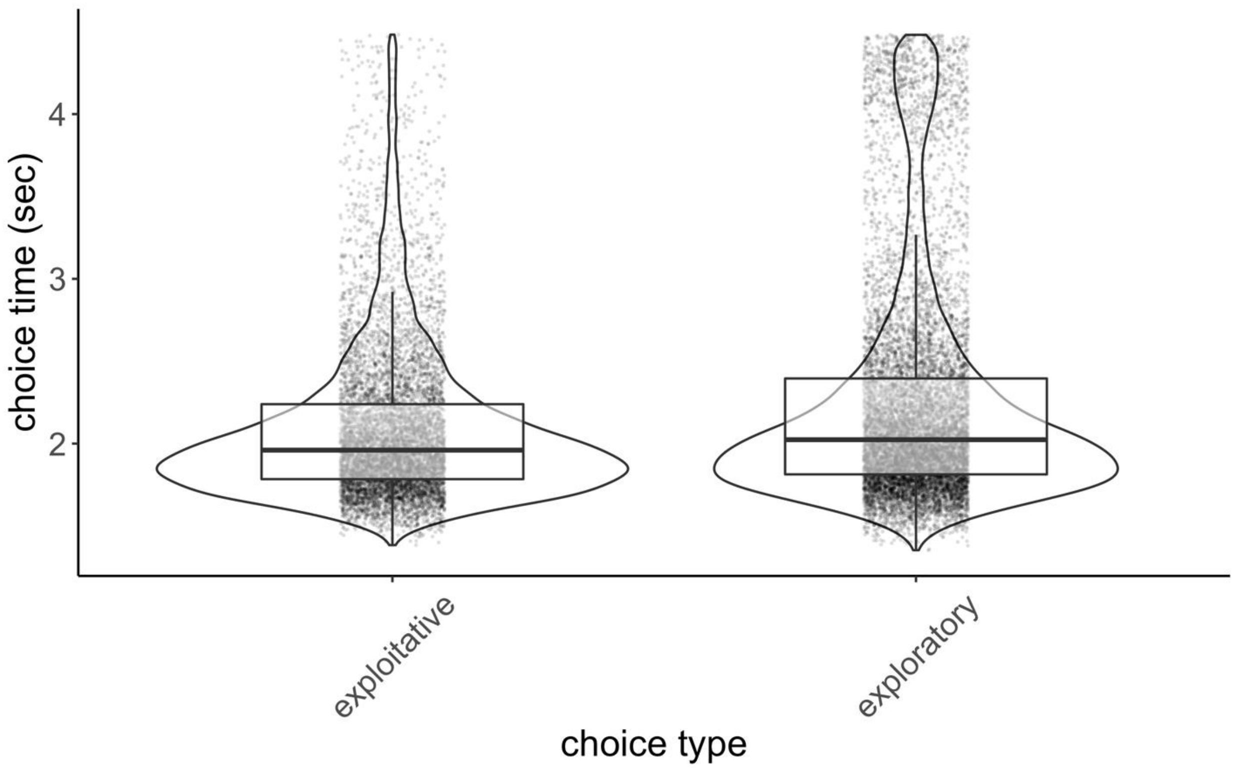
The remaining 108 participants were performing the bandit task while their eye and hand movements were recorded (mean age = 24.5, standard deviation = 4, female = 57). The task was presented using a MATLAB program on a 1920 × 1080 computer screen. On average, it took 45 minutes to finish the experiment. It had two parts, but in this study, we only use the result of the bandit part.

3.3 Analysis and Results

3.3.1 Choice time

The time taken to make a choice, either in exploration or exploitation was measured to test whether there is a difference between the time needed to choose an exploratory arm from the time to choose an exploitative one. Each person had 200 values of each mentioned measurement. As data was not distributed normally (Shapiro-Wilk test rejected the hypothesis of normality for both exploration ($W = 0.65$, $p{-}value < 2.2e{-}16$) and exploitation choice time ($W = 0.6$, $p - value < 2.2e - 16$)), a non-parametric test should be applied. Figure 3.3 shows a distribution of the time taken to make a choice in any of the exploratory and exploitative arms. Extreme outliers were removed based on Tukey's approach [61]. Tukey labels observations using the measures of the interquartile range. An extreme outlier (far-out observation) is an observation that happens outside this range multiplied by a constant of 3. Here 7.37% of the choice time observations were extreme outliers and remove from the data.

Figure 3.3 Choice time distribution in exploratory and exploitative decisions



As data were collected repeatedly for each participant and its distribution was not normal, the assumption of standard inferential models like t-test or ANOVA was not satisfied. Thus a linear mixed model from R with the lme4 package [62,63] was used as the lme4 package offers functions to fit and analyze linear mixed models [62]. This model can capture nonlinearity in data and dependency in repeated measures. Models are described using lmer function by a formula that includes fixed and random effects terms [62]. Fixed effects are explanatory variables in which we are interested in finding their effect on the dependent variables, while random effects are the factors that we are going to control, as we are not interested in their impact on the dependent variables.

Here the dependent variable was the time spent on making a choice and choosing an exploratory or exploitative choice classified as the fixed effect as we wonder to know if the type of choice affects the chosen time of each option. This variable was defined using a dummy variable representative of being exploratory or exploitative of choice. This model captured repetition and individual variations using a random effect defined by the participants' ID as each person's choice repeated 200 times. In addition, the likelihood ratio test was used to examine the significant impact of the independent factors on the dependent variable by comparing a model with its null model.

Eq. 1 summarizes the concept of this model as we planned to investigate the impact of choice type on their choice time. This model tries to fit a slope and an intercept to define the relation between a dependent variable and the fixed effect and controls for variation that each person has in her trials by the random effect.

If x_{it} held choice time for each person i in trial t, and explore was a dummy variable with the value of 1 for exploratory choice and 0 for exploitative, α will be the intercept and β the slope of the relation between these two factors while ε_{it} held within-subjects variation resulted from the task repetition and non-independence in the data.

$$x_{it} = \alpha + \beta \times explore + \varepsilon_{it} \tag{1}$$

The likelihood ratio test showed a significant effect of doing one of the exploratory or exploitative choices on the choice time ($\chi^2(1) = 392, p < .0001$).

Table 3.1 showed the coefficient of the model. The first part of the table contains predictors and the second part random effects. α as the intercept represented the average choice time in exploitative choice with its standard error in parenthesis and β as the slope shows difference of exploratory time choices with the exploitatives. The average time of this factor was obtained by the sum of the coefficient for intercept and slope (2.09+.16)). As can be seen from Table 3.1, it took significantly more time to choose an exploratory arm (2.26) than an exploitative arm (2.09).

From the random effect part, τ_{id} shows the variance for the random effect which is within participants' variation, and σ^2 depicts variation for the residuals. As mentioned, random effect controls the repetition of each trial, and residuals were everything that cannot be explained by the model using our knowledge. Intraclass Correlation Coefficient (ICC) was used here to give a sense of how much variance was explained by the random effect, and it was included 14% of the variance. N_{id} shows total number of participants.

Table 3.1: Choice time model coefficients

	choice time
Predictors	Estimates
α(Intercept)	2.096*** (0.023)
$\beta_{explore}$	0.16*** (0.008)
Random Effects	
σ^2	0.32
$\tau_{00\ id}$	0.05
ICC	0.14
N_{id}	108

$*p < .05. **p < .01. ***p < .001.$, (*Std.Error*)

3.3.2 Cross-recurrence of eye and hand movements

The simplest method to find similarities between two time series is a correlation. A critical requirement of using correlation is having a linear relationship between two variables [64]. However, there was no linear relation between the two time series, and thus non-linear tests should be used in this regard.

As mentioned earlier, the CRQA technique is used to show how strongly two time series are correlated. It quantifies cross-recurrences between two time series by extending the RQA technique, while RQA (Recurrence Quantification Analysis) finds repetition of elements or patterns in a sequence with themselves. RQA embeds a single time series in a phase-space while CRQA does that with two time series in the same phase-space.

Cross-recurrence happens when the two time series coordinates occur close to each other in the phase-space [44,53]. When the measured variable is continuous, patterns that are more complicated often appear on higher-order dynamics. The time-delayed embedding method helps to understand these dynamics [53]. Thus, the first step of this technique was reconstructing phase-space using embedding dimension and delay. Embedding dimension estimates the dimensionality of the time series, which is the number of variables that can define the dynamics of the system. The delay parameter considers sampling properties of a time series by finding points that can be used to reconstruct the missing dimensions [53]. A radius is used to test whether two values are within an interval or not to have a measure of cross-recurrence. With empirical data, this information is unknown and should be estimated. The methods were used to estimate the delay parameter and the embedding dimension was the average mutual information (AMI) and the false-nearest-neighbor. The first local minimum of both methods is used as their estimations. The estimation of the radius is not straightforward like these parameters. It is recommended to set the radius such that the resulting cross-recurrence rate lies between $\%REC = 1$ to 5%. If these properties of both time series differ, the highest value among them is chosen for each parameter [53]. In this study, the CRQA R package was used [65]. The horizontal axis of eye and hand movements over each choice and each participant was entered as two time series variables. The delay parameter was estimated using the average mutual information function for a specified number of lags for each individual eye and hand data set. Eq. 2 shows usage of the function 'mutual' from *tseriesChaos* R package [54] in this study. The lag set to 50 at first, and if nothing was found it changed to half of the length of each time series.

$$mutual(mousemovement, lag.max = 50) \tag{2}$$

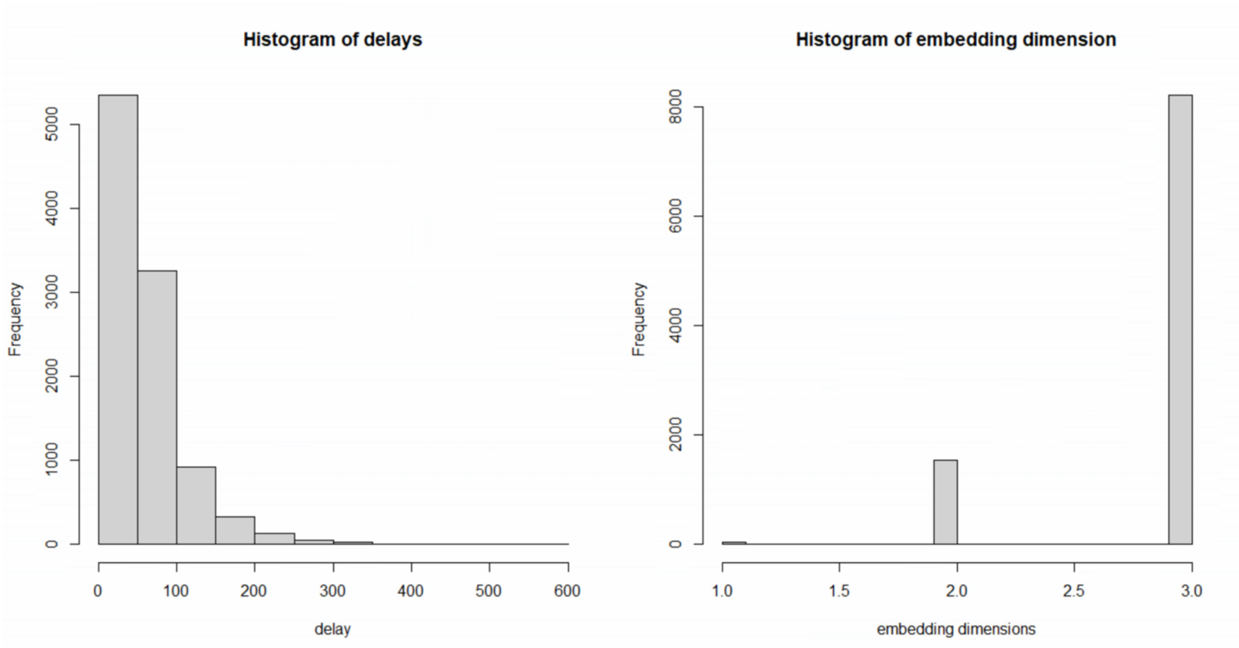
The first local minimum of this function was chosen for each data set for both hand and eye movement signals. As mutual information of points of a time series shows their dependence, finding the first local minimum is where the time series points have the most independence. Thus embedding at this point provides essential information for a new dimension in phase-space [46,53]. The false-nearest neighbor function was used for each individual hand and eye movement to estimate the embedding dimension parameter. Two points that are near each other should still close when the dimension increases. It is the core assumption of the false nearest neighbors' method. The method checks the neighbors in the increasing embedding dimensions until it finds only a negligible number of false neighbors. This dimension is chosen as the lowest embedding dimension [66]. This process was done using *false.nearest* function which is shown by Eq. 3 from *tseriesChaos* R package [67]. The function was set to embedding by 3, used delay calculated from mutual information, and t set to zero to measure all diagonals for cross-recurrence.

$$\mathit{false.nearest}(\mathit{mousemovement}, m = 3, d = \mathit{delay}, t = 0) \tag{3}$$

Again, the first local minimum of this function was chosen for each data set and each signal. The estimated value for the delay and dimension was chosen from the maximum value of both hand and mouse data. Maximum is chosen because recurrence-based analyses are robust against over-embedding [53]. This value was then averaged and rounded over all participants and trials and used for all data sets. Figure 3.4 shows the histogram of delays and embedding dimensions resulted from this method extracting from total participants[1] . As shown in this figure, the significant number of delays were in the two first bins and a significant number of embedding dimensions was in the last bin. By finding the average over these values and round the resulted number to the nearest tenth, the delay parameter was set to 64 (63.8), and the embedding dimension set to 3 (2.8).

[1] Each participant's choice contained arrays of movements, each of which had a length of at least 250 points related to the movement tracked with the frequency of 250 Hz. There were a few data points that we face error in false.nearest 'cannot allocate memory block of size~Tb' which we did not consider them in the calculation.

Figure 3.4: Histogram of embedding dimension and delays.



The radius was set to 80 by trial and error to reach a recommended range of *%REC* in most of the data points (the radiuses that *%REC* checked for and their mean and standard deviation can be seen in Table 3.2.).

Table 3.2: %REC's mean & standard deviation for different radius

radius	50	70	80	100	200	300
Mean (std)	.5 3.3	.9 4.2	1.09 4.7	1.5 5.5	5.3 9.2	10.3 11.7

Other CRQA function arguments were defined by their default values (Table 3.3). For more information, see [53]. These values of the parameters were picked such that they fit the overall sample well for both movements. The same parameters were used across all data sets in order to make comparison possible between them.

Table 3.3: CRQA inputs

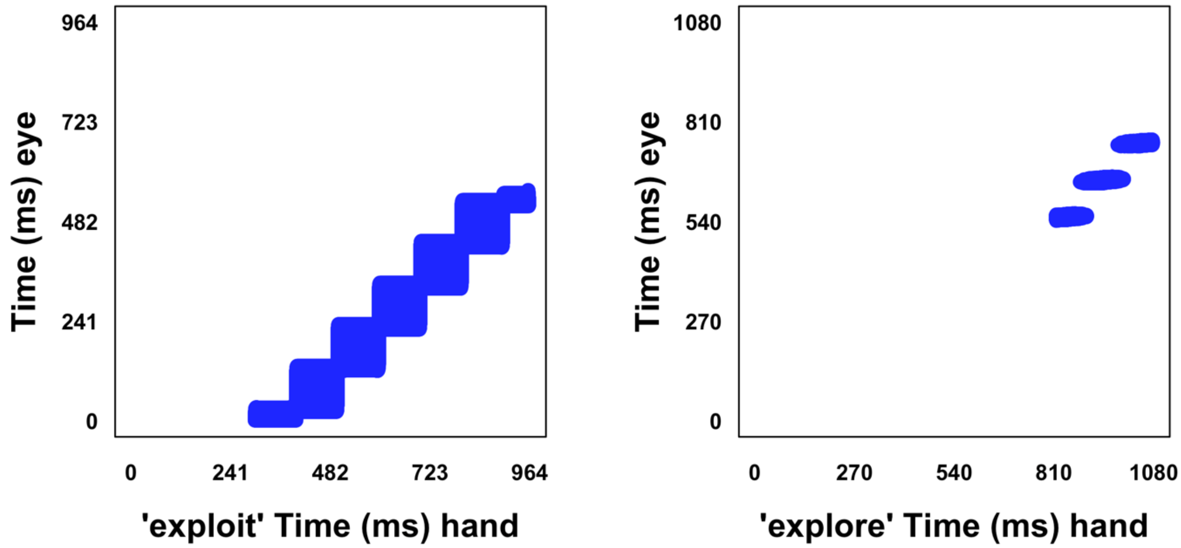
rescale	radius	normalize	mindiagline	minvertline	tw	whiteline	recpt
0	80	0	2	2	0	FALSE	FALSE

The cross-recurrence plot gives insight into analyzing the relation between eye and hand movements. Each diagonal corresponds to a particular alignment of the movement data of the eye and hand with a particular lag time between them. Researchers use the diagonal line structures to indicate a sequence of synchrony [44]. A point is plotted along the diagonal whenever the movements of the eye and hand are cross recurrent, which happens when both points in phase space are closer to each other than the designated radius. The main diagonal line shows cross-recurrence without any time lag. When eye movements are placed on the vertical axis and mouse movements are placed on the horizontal axis, the lines under the main diagonal show cross-recurrence when hand is lagging behind, while lines over the main diagonal represent when eye is lagging behind. A full cross-recurrence plot for eye-hand coordination is formed by calculating the cross-recurrence between all such alignments at all possible lag times. Figure 3.5 shows one sample of the cross-recurrence plot for exploratory (right panel) and exploitative (left panel) choices for the same individual. As can be seen from this figure in this sample, cross-recurrence is higher in exploitation (CRR = 5.06) and lower in exploration (CRR = .002).

Hands were lagging behind eyes in both pictures. Diagonal lines in cross-recurrence plot reflect sequences of revisited trajectory regions [44,65].

Here diagonal line parallel to the main diagonal shows that eye and hand states were similar at different times. Both samples are parallel to the main diagonal line, but the length of the left side line is higher than the right side, which shows higher coupling and cross-recurrence between them.

Figure 3.5: Cross-recurrence plot for two exploratory and exploitative choices with CRR = 6.74 for exploit and CRR = .035 for exploration.

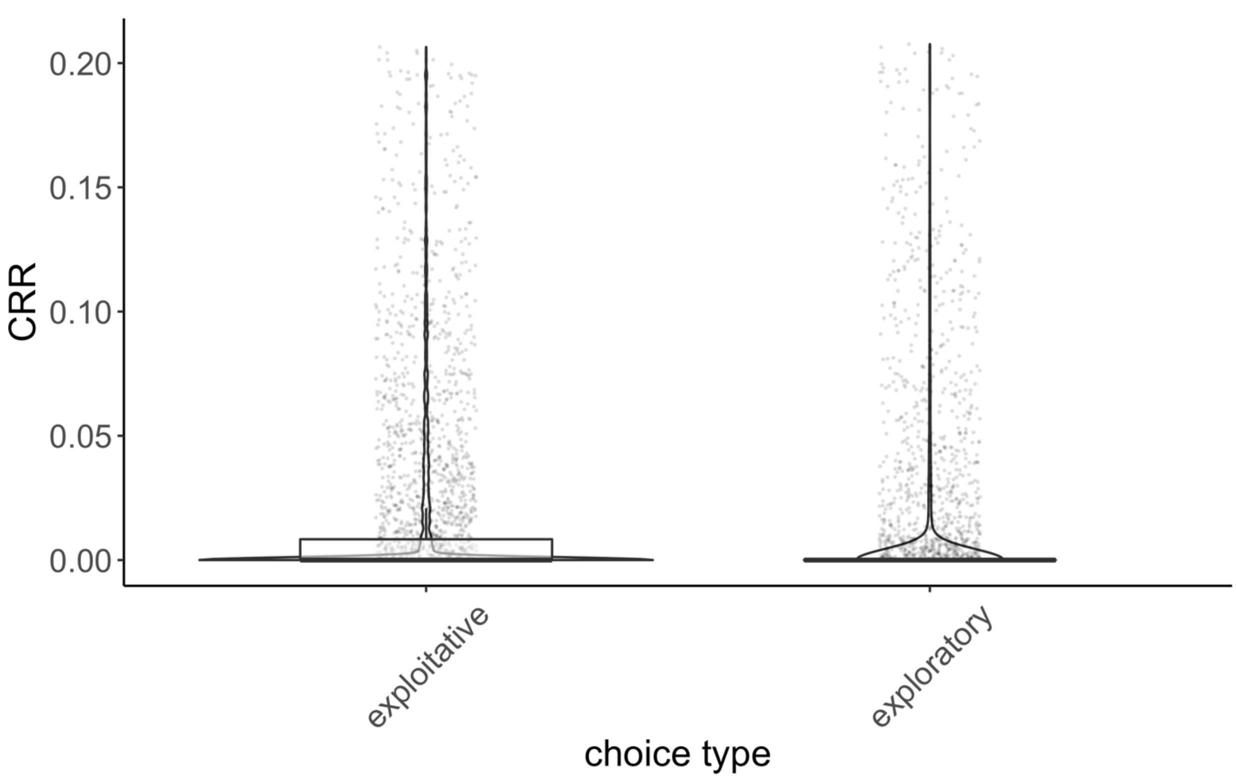


Using the CRQA package, we measured values of *CRR*, which is the percentage of cross recurrent points falling within the specified radius, which is the repetitiveness of the two time series elements. It is important to determine whether the recurrences are connected in a cross-recurrence plot because isolated points could simply result from chance. This is captured by *DET* as the proportion of cross recurrent points forming diagonal line structures. *maxL* captures the length of the most extended diagonal line segment in the plot, excluding the main diagonal. A number of the points in a cross-recurrence plot that forms adjacent diagonal line structures divided by the number of whole points on the plot shows the average diagonal length (L). It is a measure of the average length of line structures and shows the shared patterns' average duration. *ENTR* is the Shannon information entropy of diagonal line lengths longer than the minimum length, and *rENTR* is the normalized measure of entropy over the number of lines observed in the cross-recurrence plot [44,48]. Each person has 200 values of each mentioned measurement (20 periods each with 10 rounds). These values were compared using a mixed model approach to control for the random effect to know how the type of choice affects eye-hand movements' cross-recurrence properties. Figure 3.6 shows a distribution of the CRR in any of the exploratory and exploitative arms. Similar to the last part, 10.24% of CRR observations were extreme outliers and removed from the total observations.

Like the model in Eq. 1, a mixed model was used to test if there was any effect of selecting exploratory or exploitative arm on cross-recurrence of eye-hand movements. Eq. 4 shows this model, while the independent variable is a dummy variable which is one in exploration and 0 in exploit and the dependent variable is one of the mentioned CRQA measurements. The variations coming from repetition were controlled using the error term of ε_{it}.

$$CRR_{it} = \alpha + \beta \times explore + \varepsilon_{it} \qquad (4)$$

Figure 3.6 CRR distribution in exploratory and exploitative decisions



Estimated coefficients of exploratory and exploitative choice groups on these dependent variables (*CRR*, *L*, *maxL*, *ENTR*, *rENTR*) are shown in Table 3.4. In all measurements (conditional means and inside parenthesis standard deviation), except for rENTR which was not significant, exploitative choices had higher rates than exploratory ones. Thus, taking one of these choices (group effect) significantly affects the cross-recurrence values. Exploitative choices made the cross-recurrence values higher than exploratory choices.

Table 3.4: Cross-recurrence model estimation

	CRR	L	maxL	ENTR	rENTR
Predictors	Estimates	Estimates	Estimates	Estimates	Estimates
α(Intercept)	0.02***	0.68***	1.00***	0.49***	0.73***
	(0.001)	(0.037)	(0.062)	(0.026)	(0.009)
$\beta_{explore}$	-0.01***	-0.29***	-0.4***	-0.14***	0.021
	(0.01)	(0.037)	(0.05)	(0.034)	(0.014)
Random Effects					
σ^2	0.00	1.55	5.75	0.42	0.04
τ_{00id}	0.00	0.10	0.23	0.02	0.00
ICC	0.09	0.06	0.04	0.04	0.00
N	108 id	108 id	108 id	108 id	108 id

$*p < .05. **p < .01. ***p < .001.$, (*Std.Error*)

Overall, it was found CRR and choice time were positively correlated by $r(9371) = .08$, $p < .001$. For exploratory choices this correlation was $r(5701) = .09$, $p < .001$ and for the exploitative ones resulted to $r(3668) = .11$, $p < .001$. Overall, there was a weak positive correlation between time and CRR in both conditions. This result indicated that while both variables tend to increase in response to one another, their relationship was not very strong.

3.4 Conclusion

This study combines two continuous detection methods of eye and mouse movement to investigate exploration-exploitation behavior from the attention-action perspective. This expresses eye-hand coordination, considering a dynamic technique (CRQA) to give a better insight into this behavior.

There is a higher cross-recurrence rate between eye and hand movements in exploitative decisions regarding the current experimental data. Meanwhile, it takes a shorter time to choose an exploitative arm than an exploratory one on average.

Decision time can be a good measure for deviation from the ideal direct path [27–30]. As if the mouse passes a straight line, it takes faster than a zigzag line. This straight-line path of movements also shows the certainty of the choice and could approve our finding of high cross-recurrence in eye-hand coordination. The first is only a discrete outcome, but the second is a temporal activity and the relation between the input to the sensory and output to the environment.

If there is a certainty in the decision, it shows itself in the behavior and in our movements; from input to the inference system to the output. This study shows that attention and action behaviors are more correlated and connected when we are sure about our outcome of the choice than when we need to guess or calculate expected values. It is concluded that uncertainty could be contagious. It occupies our minds and affects our behavioral patterns, and makes them more chaotic and uncorrelated. Using this technique helps us test and see this synchrony in temporal behavior and discrete behavior.

Based on the mentioned result, decision time is lower for exploit and higher for explore.

People choose the exploitative arm quicker as it has higher certainty than the exploratory arm. The higher synchrony shows higher certainty and the lower choice time, that supports our hypothesis.

It is also stated in the work of Mc Namara [68] that financial returns from exploitation activities are more certain and more positive than those from exploration.

A higher rate of synchrony between eye and hand movement showed they are in-line most of the time during exploitation and follow similar pathways. It shows they behave similarly and could be revealed as certainty in the choice. While input to the inference system and output of that appeared in similar paths, it could indicate that they follow each other as the inference system is sure about its outcome and how it can be reached.

Cross-recurrence shows temporal behavior of synchrony, and decision time shows only an outcome variable. Cross-recurrence shows the relation in different time scales and goes deeper into the behavioral process, while decision time only shows a number that could result from task difficulty, fatigue, motivation, and arousal. However, if we look at this behavior into deep, we can conclude based on the eye-hand synchrony that two behaviors are in line, and decisions are made with certainty.

The limitation of this study was related to its analysis part, which was demanding in memory needed for data analysis. Therefore, for more giant data sets, it is recommended to use more powerful computers.

For future research to better reveal the temporal pattern of exploration-exploitation, it is suggested to investigate the time when the synchrony is higher. For example, is this higher at the beginning of the choice when information is collected or at the end of the choice when the decision is made. In addition, investigating whether this pattern differs in exploration vs. exploitation can give a better insight into this behavior.

References

1. Laureiro-Martínez, D., Brusoni, S., Canessa, N., & Zollo, M. (2015). Understanding the exploration–exploitation dilemma: An fMRI study of attention control and decision-making performance. *Strategic Management Journal*, *36*(3), 319–338.
2. Mehlhorn, K., Newell, B. R., Todd, P. M., Lee, M. D., Morgan, K., Braithwaite, V. A., Hausmann, D., Fiedler, K., & Gonzalez, C. (2015). Unpacking the exploration–

exploitation tradeoff: A synthesis of human and animal literatures. *Decision*, *2*(3), 191.

3. Hills, T. T., Todd, P. M., Lazer, D., Redish, A. D., Couzin, I. D., & Cognitive Search Research Group. (2015). Exploration versus exploitation in space, mind, and society. *Trends in Cognitive Sciences*, *19*(1), 46–54.
4. Walker, A., Le Pelley, M., & Beesley, T. (2017). *Exploitative and Exploratory Attention in a Four-Armed Bandit Task.* CogSci.
5. Ehinger, B. V., Kaufhold, L., & König, P. (2018). Probing the temporal dynamics of the exploration–exploitation dilemma of eye movements. *Journal of Vision*, *18*(3), 6–6.
6. Sinha, S. (2015). The exploration–exploitation dilemma: A review in the context of managing growth of new ventures. *Vikalpa*, *40*(3), 313–323.
7. Freeman, J., Dale, R., & Farmer, T. (2011). Hand in motion reveals mind in motion. *Frontiers in Psychology*, *2*, 59.
8. Rigby, D., Vass, C., & Payne, K. (2020). Opening the 'Black Box': An overview of methods to investigate the decision-making process in choice-based surveys. *The Patient-Patient-Centered Outcomes Research*, *13*(1), 31–41.
9. Colas, J. T. (2017). Value-based decision making via sequential sampling with hierarchical competition and attentional modulation. *PloS One*, *12*(10), e0186822.
10. Rabinovich, M. I., Huerta, R., Varona, P., & Afraimovich, V. S. (2008). Transient cognitive dynamics, metastability, and decision making. *PLoS Computational Biology*, *4*(5), e1000072.
11. Koop, G. J., & Johnson, J. G. (2013). The response dynamics of preferential choice. *Cognitive Psychology*, *67*(4), 151–185.
12. Banks, J., Olson, M., & Porter, D. (1997). An experimental analysis of the bandit problem. *Economic Theory*, *10*(1), 55–77.
13. Steyvers, M., Lee, M. D., & Wagenmakers, E.-J. (2009). A Bayesian analysis of human decision-making on bandit problems. *Journal of Mathematical Psychology*, *53*(3), 168–179.
14. Daw, N. D., O'doherty, J. P., Dayan, P., Seymour, B., & Dolan, R. J. (2006). Cortical substrates for exploratory decisions in humans. *Nature*, *441*(7095), 876–879.

15. Jepma, M., & Nieuwenhuis, S. (2011). Pupil diameter predicts changes in the exploration–exploitation trade-off: Evidence for the adaptive gain theory. *Journal of Cognitive Neuroscience*, *23*(7), 1587–1596.
16. Lethaus, F., & Rataj, J. (2007). Do eye movements reflect driving manoeuvres? *IET Intelligent Transport Systems*, *1*(3), 199–204.
17. Fiedler, S., & Glöckner, A. (2012). The dynamics of decision making in risky choice: An eye-tracking analysis. *Frontiers in Psychology*, *3*, 335.
18. Schulte-Mecklenbeck, M., Kühberger, A., & Ranyard, R. (2011). The role of process data in the development and testing of process models of judgment and decision making. *Judgment and Decision Making*, *6*(8), 733.
19. Horstmann, N., Ahlgrimm, A., & Glöckner, A. (2009). *How distinct are intuition and deliberation? An eye-tracking analysis of instruction-induced decision modes*. Preprints of the Max Planck Institute for Research on Collective Goods.
20. Stewart, N., Hermens, F., & Matthews, W. J. (2016). Eye movements in risky choice. *Journal of Behavioral Decision Making*, *29*(2–3), 116–136.
21. Kuechenmeister, C. A., Linton, P. H., Mueller, T. V., & White, H. B. (1977). Eye tracking in relation to age, sex, and illness. *Archives of General Psychiatry*, *34*(5), 578–579.
22. Radant, A. D., & Hommer, D. W. (1992). A quantitative analysis of saccades and smooth pursuit during visual pursuit tracking: A comparison of schizophrenics with normals and substance abusing controls. *Schizophrenia Research*, *6*(3), 225–235.
23. ROBBINS, A., & HOUT, M. C. (2015). LOOK INTO MY EYES. *Scientific American Mind*, *26*(1), 54–61.
24. Jacob, R. J., & Karn, K. S. (2003). Eye tracking in human-computer interaction and usability research: Ready to deliver the promises. In *The mind's eye* (pp. 573–605). Elsevier.
25. Ehmke, C., & Wilson, S. (2007). *Identifying web usability problems from eyetracking data*.
26. Choi, E., Kim, C., & Lee, K. C. (2020). Consumer Decision-Making Creativity and Its Relation to Exploitation–Exploration Activities: Eye-Tracking Approach. *Frontiers in Psychology*, *11*.

27. Hehman, E., Stolier, R. M., & Freeman, J. B. (2015). Advanced mouse-tracking analytic techniques for enhancing psychological science. *Group Processes & Intergroup Relations*, *18*(3), 384–401.
28. Barca, L., & Pezzulo, G. (2015). Tracking second thoughts: Continuous and discrete revision processes during visual lexical decision. *PloS One*, *10*(2), e0116193.
29. O'Hora, D., Dale, R., Piiroinen, P. T., & Connolly, F. (2013). Local dynamics in decision making: The evolution of preference within and across decisions. *Scientific Reports*, *3*(1), 1–9.
30. Koop, G. J., & Johnson, J. G. (2011). Response dynamics: A new window on the decision process. *Judgment & Decision Making*, *6*(8).
31. Dshemuchadse, M., Scherbaum, S., & Goschke, T. (2013). How decisions emerge: Action dynamics in intertemporal decision making. *Journal of Experimental Psychology: General*, *142*(1), 93.
32. Franco-Watkins, A. M., & Johnson, J. G. (2011). Applying the decision moving window to risky choice: Comparison of eye-tracking and mousetracing methods. *Judgment and Decision Making*, *6*(8), 740.
33. Raghunath, V., Braxton, M. O., Gagnon, S. A., Brunyé, T. T., Allison, K. H., Reisch, L. M., Weaver, D. L., Elmore, J. G., & Shapiro, L. G. (2012). Mouse cursor movement and eye tracking data as an indicator of pathologists' attention when viewing digital whole slide images. *Journal of Pathology Informatics*, *3*.
34. Furtner, M., & Sachse, P. (2008). *The psychology of eye-hand coordination in human computer interaction*. *8*, 144–149.
35. Pelz, J., Hayhoe, M., & Loeber, R. (2001). The coordination of eye, head, and hand movements in a natural task. *Experimental Brain Research*, *139*(3), 266–277.
36. Sailer, U., Eggert, T., & Straube, A. (2005). Impaired temporal prediction and eye–hand coordination in patients with cerebellar lesions. *Behavioural Brain Research*, *160*(1), 72–87.
37. Binsted, G., Chua, R., Helsen, W., & Elliott, D. (2001). Eye–hand coordination in goal-directed aiming. *Human Movement Science*, *20*(4–5), 563–585.
38. Crawford, J. D., Medendorp, W. P., & Marotta, J. J. (2004). Spatial transformations for eye–hand coordination. *Journal of Neurophysiology*.

39. Freeman, J. B. (2018). Doing psychological science by hand. *Current Directions in Psychological Science*, *27*(5), 315–323.

40. Demšar, U., & Çöltekin, A. (2017). Quantifying gaze and mouse interactions on spatial visual interfaces with a new movement analytics methodology. *PloS One*, *12*(8), e0181818.

41. Schneider, I. K., & Schwarz, N. (2017). Mixed feelings: The case of ambivalence. *Current Opinion in Behavioral Sciences*, *15*, 39–45.

42. Gillebaart, M., Schneider, I. K., & De Ridder, D. T. (2016). Effects of trait self-control on response conflict about healthy and unhealthy food. *Journal of Personality*, *84*(6), 789–798.

43. Forstmann, B. U., Ratcliff, R., & Wagenmakers, E.-J. (2016). Sequential sampling models in cognitive neuroscience: Advantages, applications, and extensions. *Annual Review of Psychology*, *67*, 641–666.

44. Coco, M. I., & Dale, R. (2014). Cross-recurrence quantification analysis of categorical and continuous time series: An R package. *Frontiers in Psychology*, *5*, 510.

45. Horstmann, A., & Hoffmann, K.-P. (2005). Target selection in eye–hand coordination: Do we reach to where we look or do we look to where we reach? *Experimental Brain Research*, *167*(2), 187–195.

46. Wallot, S., & Mønster, D. (2018). Calculation of average mutual information (ami) and false-nearest neighbors (fnn) for the estimation of embedding parameters of multidimensional time series in matlab. *Frontiers in Psychology*, *9*, 1679.

47. Richardson, D. C., & Dale, R. (2005). Looking to understand: The coupling between speakers' and listeners' eye movements and its relationship to discourse comprehension. *Cognitive Science*, *29*(6), 1045–1060.

48. Wallot, S., Mitkidis, P., McGraw, J. J., & Roepstorff, A. (2016). Beyond synchrony: Joint action in a complex production task reveals beneficial effects of decreased interpersonal synchrony. *PloS One*, *11*(12), e0168306.

49. Demos, A. P., Chaffin, R., & Kant, V. (2014). Toward a dynamical theory of body movement in musical performance. *Frontiers in Psychology*, *5*, 477.

50. Marwan, N., Romano, M. C., Thiel, M., & Kurths, J. (2007). Recurrence plots for the analysis of complex systems. *Physics Reports*, *438*(5–6), 237–329.

51. Giuliani, A., Benigni, R., Zbilut, J. P., Webber, C. L., Sirabella, P., & Colosimo, A. (2002). Nonlinear signal analysis methods in the elucidation of protein sequence− structure relationships. *Chemical Reviews*, *102*(5), 1471–1492.

52. Webber Jr, C. L., & Zbilut, J. P. (1994). Dynamical assessment of physiological systems and states using recurrence plot strategies. *Journal of Applied Physiology*, *76*(2), 965–973.

53. Wallot, S., & Leonardi, G. (2018). Analyzing multivariate dynamics using cross-recurrence quantification analysis (crqa), diagonal-cross-recurrence profiles (dcrp), and multidimensional recurrence quantification analysis (mdrqa)–a tutorial in r. *Frontiers in Psychology*, *9*, 2232.

54. Lyby, M. S., Mehlsen, M., Jensen, A. B., Bovbjerg, D. H., Philipsen, J. S., & Wallot, S. (2019). Use of Recurrence Quantification Analysis to Examine Associations Between Changes in Text Structure Across an Expressive Writing Intervention and Reductions in Distress Symptoms in Women With Breast Cancer. *Frontiers in Applied Mathematics and Statistics*, *5*, 37.

55. Fusaroli, R., Konvalinka, I., & Wallot, S. (2014). Analyzing social interactions: The promises and challenges of using cross recurrence quantification analysis. In *Translational recurrences* (pp. 137–155). Springer.

56. Kiani, R., Corthell, L., & Shadlen, M. N. (2014). Choice certainty is informed by both evidence and decision time. *Neuron*, *84*(6), 1329–1342.

57. Orquin, J. L., Ashby, N. J., & Clarke, A. D. (2016). Areas of interest as a signal detection problem in behavioral eye-tracking research. *Journal of Behavioral Decision Making*, *29*(2–3), 103–115.

58. SR Research. (2009). *EyeLink 1000 User Manual*.

59. Kleiner, M., Brainard, D., & Pelli, D. (2007). *What's new in Psychtoolbox-3?*

60. Developers, S. (2013). Signal: Signal processing. *URL: Http://R-Forge. r-Project. Org/Projects/Signal*.

61. Tukey, J. W. (1977). *Exploratory data analysis* (Vol. 2). Reading, Mass.

62. Bates, D., Mächler, M., Bolker, B., & Walker, S. (2014). Fitting linear mixed-effects models using lme4. *ArXiv Preprint ArXiv:1406.5823*.

63. Winter, B. (2013). Linear models and linear mixed effects models in R with linguistic applications. *ArXiv Preprint ArXiv:1308.5499*.

64. Benesty, J., Chen, J., Huang, Y., & Cohen, I. (2009). Pearson correlation coefficient. In *Noise reduction in speech processing* (pp. 1–4). Springer.

65. Coco, M. I., Mønster, D., Leonardi, G., Dale, R., & Wallot, S. (2020). Unidimensional and Multidimensional Methods for Recurrence Quantification Analysis with crqa. *ArXiv Preprint ArXiv:2006.01954*.

66. Krakovská, A., Mezeiová, K., & Budáčová, H. (2015). Use of false nearest neighbours for selecting variables and embedding parameters for state space reconstruction. *Journal of Complex Systems*, *2015*.

67. Di Narzo, A. (2019). Di Narzo. *F. TseriesChaos: Analysis of Nonlinear Time Series*, *859*, 860.

68. Mc Namara, P., & Baden-Fuller, C. (2007). Shareholder returns and the exploration–exploitation dilemma: R&D announcements by biotechnology firms. *Research Policy*, *36*(4), 548–565.