DYNAMICAL ASPECTS OF DECISION MAKING UNDER UNCERTAINTY

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KEMAL TAŞKIN

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Submitted by **KEMAL TAŞKIN** in partial fulfillment of the requirements for the degree of **Doctor of Philosophy in Cognitive Sciences Middle East Technical University** by,

Prof. Dr. Nazife Baykal ____________________
Director, **Informatics Institute**

Assist. Prof. Dr. Cengiz Acartürk ____________________
Head of Department, **Cognitive Sciences**

Assist. Prof. Dr. Didem Gökçay ____________________
Supervisor, **Medical Informatics**

Examining Committee Members:

Assoc. Prof. Dr. Erol Şahin ____________________
Computer Engineering, Middle East Technical University

Assist. Prof. Dr. Didem Gökçay ____________________
Medical Informatics, Middle East Technical University

Assist. Prof. Dr. Murat Perit Çakır ____________________
Cognitive Sciences, Middle East Technical University

Assist. Prof. Dr. Albert Ali Salah ____________________
Computer Engineering, Boğaziçi University

Assist. Prof. Dr. Bilge Say ____________________
Digital Game Design, İpek University

Date: 02.02.2016

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this wok.

Name, Last name : **Kemal Taşkın**

Signature : ____________________

ABSTRACT

DYNAMICAL ASPECTS OF DECISION MAKING UNDER UNCERTAINTY

Taşkın, Kemal
Ph.D., Department of Cognitive Sciences
Supervisor: Assist. Prof. Dr. Didem Gökçay

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Decision making is defined as the mental process of choosing among a set of alternatives. Although several aspects of decision making have been investigated so far in cognitive science, dynamics of this process as a whole remained to be studied in detail. In this context, we investigated the effects of consecutive decisions on the current decision in a decision making task under uncertainty. In the attempt of elaborating these effects, we analyzed responses of participants to risky choices in two experiments by two different approaches. In the first experiment, in order to understand participants' physiological expressions under risky choices, we utilized TOBII T120 eye-tracker and collected pupillary responses of participants. In the second experiment, we collected participants' response times to given decisions. We analyzed our results with a slightly modified version of Balloon Analog Risk Task (BART). Participants were also subjected to a survey, DOSPERT, prior to the experiments to monitor and distinguish their individual risk taking attitudes. In addition, in two supplementary experiments using Cups Task and Cambridge Gambling Task (CGT), particular aspects of the proposed system were shown to generalize beyond BART. Finally, a simulation was also developed and run in order to elaborate on whether participants' decision strategies indicated a learning of the task. Our thorough analysis of participants' responses and the results of the simulation indicated a dynamic system consisting of momentary risk taking and risk aversive states. Participants' pupil dilation magnitudes were found to be predictable from this dynamical model, abstracted from their consecutive decisions. Natural risk attitudes, extracted from the survey had no statistically significant effect on the results. Our study indicated that risk taking states have important roles on the understanding of decision making tasks. In summary, our findings suggests a model that fuses emotional and cognitive aspects within risky uncertain decisions.

Keywords: Decision Making, Risk Taking, Pupil Dilation, Dynamic Systems

ÖZ

BELİRSİZLİK DURUMLARINDA KARAR VERME İŞLEMİNİN DİNAMİK BOYUTU

Taşkın, Kemal
Doktora, Bilişsel Bilimler Bölümü
Tez Yöneticisi: Yrd. Doç. Dr. Didem Gökçay

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Karar verme, bir dizi alternatif arasından seçim yapma esnasındaki zihinsel süreç olarak tanımlanır. Bilişsel bilimler bünyesinde, karar vermenin birçok ayrıntısı çalışılmış olmakla birlikte bu sürecin bütünsel dinamikleri henüz çalışılacak bir alan olarak durmaktadır. Bu çerçevede, biz arka arkaya verilen kararların mevcut kararlara olan etkisini araştırdık. Bu etkiyi inceleyebilmek adına iki farklı yaklaşımla yaptığımız iki deney gerçekleştirdik. İlk deneyde, katılımcıların riskli alternatiflere verdikleri fizyolojik tepkileri, TOBII T120 göz izleme cihazını kullanarak anlamayı hedefledik. İkinci deneyde, katılımcıların yaptıkları seçimlerin tepki sürelerini inceledik. Bu deneylerde analizler Balloon Analog Risk Task adlı deney paradigmasının özelleştirilmiş bir versiyonunu kullanarak yapıldı. Katılımcıların kişisel risk alma eğilimlerini ölçmek ve analiz etmek için deneylerden önce buna yönelik DOSPERT adlı anket uygulandı. Ek olarak, farklı katılımcılardan oluşan iki farklı gruba Cups Task ve Cambridge Gambling Task (CGT) paradigmaları kullanılarak iki deney yapıldı. Son olarak, katılımcıların karar verme stratejilerinde öğrenme olup olmadığını tespit etmek amacıyla bir de simülasyon geliştirildi. Toplanan ve incelenen bu verilerin geneline bakıldığında bu verilerin risk alma ve riskten kaçınma durumlarından oluşan bir dinamik sisteme işaret ettiği görüldü. Bu dinamik model ile katılımcıların mevcut kararları, onların önceki kararları ve göz bebeği açıklıkları üzerinden tahmin edilebilir olmaktadır. Yapılan anket ile elde edilen bireysel risk alma eğilimlerinin ise istatistiksel olarak anlamlı bir etkisinin olmadığı görüldü. Bu çalışma göstermektedir ki, değişen risk alma durumları karar verme deneylerinin anlaşılmasında önemli bir rol oynamaktadır. Özetle, ortaya koyduğumuz bulgular belirsizlik altında risk alma durumları için duyuşsal ve bilişsel etkileri birleştirecek bir modeli işaret etmektedir.

Anahtar Sözcükler: Karar Verme, Risk Alma, Göz Bebeği Büyümesi, Dinamik Sistemler

With the hopes that this work may in some way contribute to
future scientific studies...

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LIST OF ABBREVIATIONS

BART	Balloon Analog Risk Task
BIAS	Behavioral Investment Allocation Strategy
CCT	Columbia Card Task
CGT	Cambridge Gambling Task
DLPFC	Dorso-Lateral Pre-Frontal Cortex
DMPFC	Dorso-medial Pre-Frontal Cortex
DOSPERT	Domain Specific Risk Taking
EEG	Electro-Encephalography
EV	Expected Value
fMRI	Functional Magnetic Resonance Imaging
fNIRS	Functional Near-Infrared Spectroscopy
GLM	General Linear Model
GUI	Graphical User Interface
HCI	Human-Computer Interaction
HMM	Hidden Markov Model
IGT	Iowa Gambling Task
ISI	Inter-Stimulus Interval
LC	Locus Coeruleus
m-BART	Modified Balloon Analog Risk Task
NA	Noradrenaline
NAcc	Nucleus Accumbens
OFC	Orbito-Frontal Cortex
PET	Positron Emission Tomography
POG-VOG	Photo-Video Oculography
rTMS	Repetitive Transcranial Magnetic Stimulation
SCR	Skin Conductance Response
SDK	Software Development Kit
SMH	Somatic Marker Hypothesis
VMPFC	Ventro-medial Pre-Frontal Cortex
WCST	Wisconsin Card Sorting Task

CHAPTER 1

INTRODUCTION

Every day, we constantly arrive at situations where we are required to choose among a set of alternatives. Simple or complex, these choices produce outcomes that have minor or major implications to our future lives. Even when there are uncertainties among the alternatives, in each decision, we decide always on what we believe to be the best for us.

Study of decision making is a very broad and a complex topic of research, with a long history dating back to the early studies of behavioral economics (Bernoulli, 1954; Camerer C. , 1999; Camerer & Loewenstein, 2004). Several studies from different disciplines, most of which remain out of the scope of this thesis, investigated the effects of past experiences (Evans, Barston, & Pollard, 1983; West, Toplak, & Stanovich, 2008), cognitive biases (Shah & Oppenheimer, 2008), escalation of commitment (Juliusson, Karlsson, & Garling, 2005), tendency to avoid past mistakes (Zeelenberg, 1999) and person's age (Finucane, Mertz, Slovic, & Schmidt, 2005; Kovalchik, Camerer, Grether, Plott, & Allman, 2005). To conclude, decision making is a multi-disciplinary topic that comprises of studies from several disciplines (for general reviews, see (Plous, 1993; Paulus, 2005; Edwards & Fasolo, 2001)).

In the particular field of cognitive science, decision making is defined as the mental process of choosing among a set of alternatives. Study of this process spans an area including its cognitive, neural and emotional aspects (for general reviews on the history of decision making in cognitive science, see (Fellows, 2004; Ernst & Paulus, 2005; Paulus, 2005)).

A subset of these studies involves decision making under uncertainty. In such studies, participants are subjected to make several consecutive decisions in laboratory environments through experiments where win/lose probabilities and reward/punishment amounts are unknown or vague (see Table 1 for definitions in decision making terminology that is referenced here). Several experimental paradigms (tasks) were proposed and used to study particular aspects of it (see (Schonberg, Fox, & Poldrack, 2011; Figner & Weber, 2011; Platt & Huettel, 2008) for reviews of such studies and tasks that are used in this context). These paradigms vary with respect to their characteristics such as giving immediate win/lose feedbacks after trials, allowing or limiting the effects of learning (of optimal winning combinations or strategies), distribution of choices, or participants earning actual monetary rewards at the end of the task (a list and a brief summary of a subset of these tasks will be given in Chapter 3).

Table 1: Decision Making Terminology. This table comprises of some of the important terminology in the context of cognitive science, and their short definitions.

Decision making	The mental process of choosing among a set of alternatives. In decision making studies, participants are given a set of alternatives for the participants to choose from. Their behavior and/or neurophysiological responses are observed and interpreted with respect to the hypothesis and the task design.
Reward	Choices in decision making tasks may contain rewards or (punishments) with respect to the task design. Participant may earn a reward upon making particular choices. Depending on the task design, these rewards can be permanent or temporary. They can convert to actual monetary rewards or not. Participants can be notified immediately after the choice or at the end of the experiment.
Risk taking	When the choices of a decision making does not provide guaranteed rewards, participants must make their decisions by taking risks. Depending on the task design, partial information, such as the probabilities of winning or other types of information can be provided.
Uncertainty	If a risk taking situation does not provide explicit information on the winning probabilities and rewards, this situation is referred as uncertainty.
Learning	In a decision making task under uncertainty, if the participants are provided with immediate feedbacks after choices, they may learn the basics of the task, such as the probabilities of winning or reward amounts. When a task is being learned, participants eventually make choices to maximize their rewards.

The variation of the selection criteria (of reward/punishment amounts, win/lose probabilities or choice distributions) in this group of studies help reveal the characteristics of risk taking under uncertainty (risk taking for short[1]).

[1] Risk taking is, in common sense, independent of uncertainty. Even though everything about the selection criteria is known, one can claim that the person is taking a risk in every choice. However, both terms are being used variably among studies and reviews (Loewenstein, Weber, Hsee, & Welch, 2001;

Utilization of neuroimaging or eye tracking techniques further enabled researchers to study individual differences among people and emotional aspects that influence and guide risk taking behavior (for reviews see; (Schonberg, Fox, & Poldrack, 2011; Weber & Johnson, 2008)).

One particular aspect, the changes in participants' emotional states throughout a task, remains as an area of study that did not draw enough attention in the literature of decision making under uncertainty. For instance, studies that are referenced in the literature review and in the aforementioned reviews (Schonberg, Fox, & Poldrack, 2011; Weber & Johnson, 2008) did not take this aspect into account in their data analyses. The focus of these studies, in this context, was the general risk taking attitudes of participants. Participants were generally assumed to make decisions without changing or switching their emotional states within the course of the experiment. Therefore, in these studies, each trial in the task was then analyzed independently.

To clarify and to note one exception, there are special cases where participants can and do change their decision strategies. In a decision making task where learning (of the reward/punishment amounts, win/lose probabilities, etc.) takes place, participants start developing better winning strategies. They gradually (either implicitly or explicitly) learn the task design and make decisions with respect to this knowledge. Such strategy developing can also be observed over their overt and bodily responses. When participants' attention to choices are tracked throughout a decision making task, it was observed that their learning of the task (i.e. the win/lose probabilities and gain modifiers) effect their neurophysiological responses and response times, allowing them do more robust and fast decisions (Orquin & Mueller Loose, 2013; de Gee, Knapen, & Donner, 2014).

However, when an optimal winning strategy is difficult to be learned and it is provided that the task is emotionally engaging (by task design, immediate feedback, etc.), then the participants seem to exhibit a different kind of change in their responses, especially with respect to the immediate outcomes of their previous responses. Moreover, unlike the learning behavior, this change does not have a direction to a better strategy or an understanding of the task. Participants appear to switch their momentary risk taking attitudes; they either happen to be in a more risk taking state or a more risk aversive state.

Main objective of this thesis and executed experiments is to understand this temporal nature of decision making. We propose that the outcomes of previous decisions have an effect on the current decision. We hypothesize that this phenomenon can be represented as a dynamical system; temporal states that the participants are in (risk

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Wu, Zhang, & Gonzalez, 2005). For the sake of simplicity, we will be referring to risk taking under uncertainty as risk taking throughout the thesis.

taking / risk aversive), a heuristic value that represents these states, and a transition function that points the moments of state transition.

In this study, with a novel decision making task, we attempted to observe this temporality. We collected pupillary response from participants as a verification of the emotional states. In addition, we performed a survey on natural risk taking tendencies to account for individual differences among participants.

1.1. The Aim of the Thesis, Research Questions and Hypotheses

Decision making tasks in neuroeconomics are sequential by design. Several decisions are consecutively presented to the participants, and later analyzed as a directed sequence of events (Figure 1). In general, risk taking strategy of an individual is believed to settle at some instance during the task (perhaps after a short period of warm-up), and does not change any further. Alternatively, the task is being learned and the individual develops a strategy to make more profitable decisions.

However, in the tasks that probabilities and gain/loss amounts are not openly given or not easily learned, and engage participants emotionally (via rewards or feedback), this may not be the case. We believe that immediate win/lose outcomes in such tasks change momentary emotional states (or risk taking states) of the participants. These changes then lead participants change behavior for the upcoming decisions.

This aspect of sequential decision making task comes from the affective nature of decision making. The idea of the current outcome effecting the next decision has long been a subject of study in decision making (for a general review; see (Loewenstein, Weber, Hsee, & Welch, 2001; Figner, et al., 2010; Figner & Weber, 2011)). The near-miss phenomenon serves as an example. The near-miss outcomes (negative outcomes that are only proximal to winning) increase gambling propensity in the upcoming decisions (Reid, 1986; Clark, Lawrence, Astley-Jones, & Gray, 2009). We believe that an investigation of changing risk taking attitudes (that is the result of the changing emotional states) can also contribute to these studies.

The aim of the study is to investigate and to model the nature of this emotional aspect. We believe that this cannot solely be explained by a recency effect. Rather, the situation should be described as a dynamic system, where the decision making

Figure 1: Simplification of the sequence of a decision making task. Participant makes a decision (with an optional overt response) and it returns an outcome (with an optional feedback). This sequence continues for a finite number of times by presenting similar or different choices in the context of the experimental paradigm.

behavior arises from risk taking states, and that these states can change with respect to a transition function[2].

Our objective is to model this dynamic character, as summarized in this section. To clarify, our understanding and use of the dynamic character is simply defined as an interchanging set of emotional states, their effect on participant decisions and a transition function that is a result of participant decisions and their outcomes.

One last remark should be that the very same phrase of dynamicity is also used to explain computational models of decision making for a single decision (Busemeyer & Johnson, 2005; Glöckner & Herbold, 2011; Fiedler & Glöckner, 2012); the dynamic analysis of eye movements in individual decisions (Orquin & Mueller Loose, 2013; de Gee, Knapen, & Donner, 2014); and also for the temporal progress of strategy developing in decision making tasks without uncertainty (Orquin, Bagger, & Mueller Loose, 2013). These areas of research will remain out of the scope of this study.

To summarize, the three motivational research questions and the hypotheses of the thesis are as follows:

In a decision making task under uncertainty;

Research Question 1. What is the nature of the effect of previous decisions and their outcomes to the current decision?

> ***Hypothesis 1.*** Participants are either in a more risk taking or a more risk aversive emotional state. These states can be modelled as dynamic system, and the predictions of this system can be observed via neurophysiological responses.
>
> ***Hypothesis 2.*** Previous decisions and their outcomes can change the emotional states. These changes will be observed via tracking changes in neurophysiological responses.

Research Question 2. What is the underlying factor in the participants' differential responses to the same stimuli throughout the task?

> ***Hypothesis 3.*** When presented with an identical trial more than once, participants will prefer the less risky alternative when they are in a risk aversive state and the more risky alternative when they are in a risk taking state.

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[2] See (van Gelder, 1998; Beer, 2000; Haken, Kelso, & Bunz, 1985; Kelso & Zanone, 2002; Cessac, 2010) for an incomplete list of other uses of dynamic systems in cognitive science.

Research Question 3. Do individual differences on risk taking have an overall effect?

> ***Hypothesis 4.*** Natural risk taking attitudes has a general effect that distinguishes one individual from another. Participants with higher risk taking tendencies will appear in the risk taking state more.

Task designs, results and analyses that are provided in the body of the thesis will be referring to these research questions and hypotheses further on.

1.2. The Organization of the Thesis

First chapter is a general introduction of the study. The basic terminology of decision making and risk taking is introduced in detail. Following the introduction, this chapter concludes by presenting the motivation, **research questions** and **hypotheses** of the study.

Second chapter gives an overview of the pupillary response. In the first experiment that will be presented, the pupillary response is used as the bodily response as an indicator of emotional arousal and risk taking. Therefore this chapter comprises of a brief summary of the pupillary response anatomy, its significance on scientific research, measurement techniques, data processing techniques and limitations. It concludes with our reasoning on the choice of pupillary response in our study.

Third chapter starts with a short background on the history of decision making. Behavioral economics and neuroeconomics are summarized to give a general idea of the development of decision making studies. It is followed by a short introduction on neuroeconomics and neural underpinnings of decision making under uncertainty and emotions. Contributions of decision making tasks to this literature are given as a table. In the literature survey that follows, an introduction to the task that is primarily used in this study is given: **Balloon analog Risk Task** (BART). In addition, Iowa Gambling Task (IGT) and Columbia Card Task (CCT) are introduced because of their references later in discussion. Cups Task and Cambridge Gambling Task (CGT) are briefly introduced, because of their uses in the study. Finally, this chapter concludes with our reasoning on the choice of BART in the thesis.

Fourth chapter comprises of the experimental setups and the methods that are executed to verify the hypotheses. **Modified BART** (m-BART) is described along with its similarities and differences from BART. A preliminary exploratory study, that was executed to fine-tune the m-BART, is also described and its impacts are briefly discussed. Finally, a list of experiments and studies are given as a table. Following this list, experiment setups, participants, materials and methods are explained in detail.

Fifth chapter consists of the results of the experiments. Analyses of these results and all statistical tests are given in this chapter in detail. The major analysis is on the momentary emotional states that we referred as risk taking states. The mathematical foundations of these states are described in this chapter. Furthermore, other possible hypotheses are also addressed and their results are also given in contrast.

Finally the **sixth chapter** involves a discussion on the results and of the hypotheses. Possible implications and ideas as future work are also discussed in this chapter. This final chapter also includes a summary on the limitations of the study. A conclusion is provided as a summary of the findings of the thesis.

Findings of this research was partially presented earlier in Affective Computing and Intelligent Interaction Conference in Xi'an, China (Taskin & Gokcay, 2015) and submitted to International Journal of Human Computer Interactions in February, 2016 (Taskin & Gokcay, 2016).

CHAPTER 2

BASICS OF PUPILLARY RESPONSE

The results presented in this thesis have been obtained by collecting pupillary response. This chapter comprises of an introduction to the basics of pupillary response; the anatomy of the iris muscles, the scientific implications of pupillary response, data collection techniques, and its limitations.

2.1. Anatomy of the Pupil Response

The pupil is the hole, which is located in the center of the iris of the eye. It allows the light information pass through the eye. Iris has two muscles that control the size of the pupil. Circular sphincter pupillae muscle constricts the pupil (miosis) and the radial dilator pupillae muscle dilates it (mydriasis) (Figure 2). These muscles respond to all sensory stimuli, regardless of their modalities (visual, tactile, auditory, gustatory and olfactory) (Beatty & Lucero-Wagoner, 2000).

Both sympathetic and parasympathetic pathways of the autonomic nervous system control iris muscles and therefore pupillary responses. Parasympathetic innervation begins in the Edinger Westphal oculomotor complex/nucleus in the midbrain. It then travels to oculomotor nerve (third cranial nerve), to the ciliary ganglion and finally to the sphincter pupillae. Sympathetic innervation begins in the hypothalamus, travels

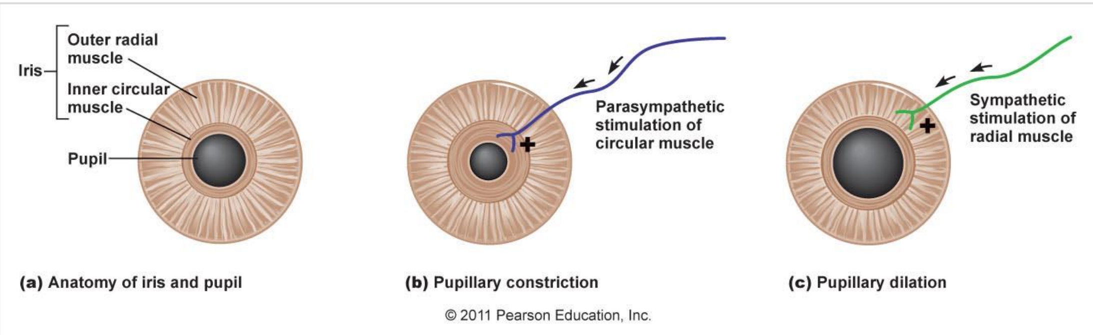


Figure 2: Iris muscles and corresponding pupillary responses: Constriction and dilation.

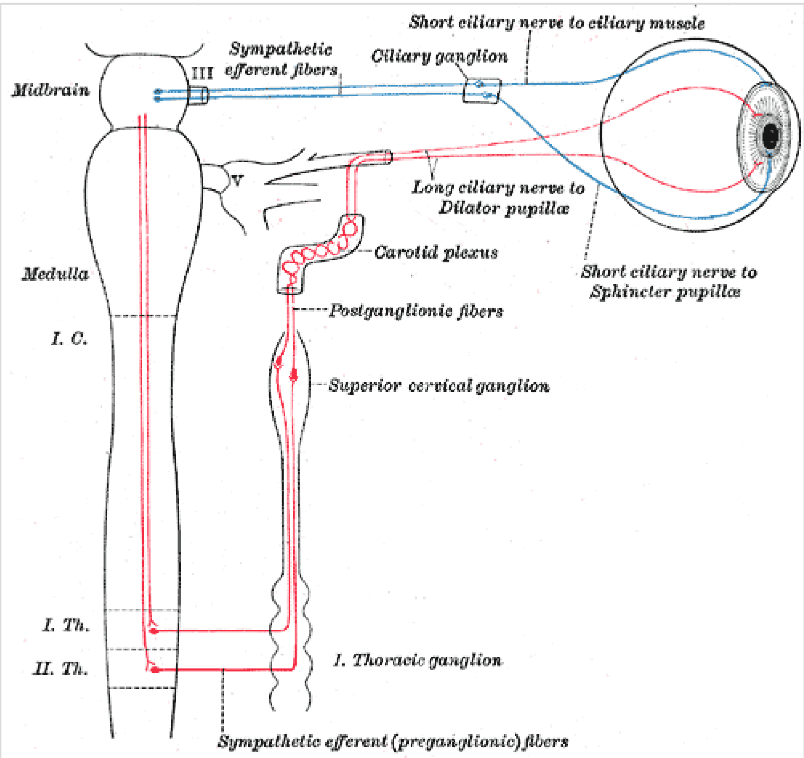


Figure 3: Sympathetic and parasympathetic pathways and the corresponding neural structures that control pupillary responses.

through the spinal cord, then to the superior cervical ganglion and finally to the dilator pupillae (Figure 3).

Nature of the effect of these two parts of the autonomic nervous system on pupillary response differs with respect to the muscles that are controlled. Activity in the dilator muscles increases with respect to the increase in sympathetic activity. On the other hand, inhibition of the parasympathetic system also causes dilation by minimizing the activity in the sphincter muscle. The parasympathetic nervous system is responsible from digestion, relaxation, sleep and the sympathetic nervous system kicks in for alertness, and survival related fight-or-flight response.

2.2. Pupil Dilation Literature

2.2.1. Pupillary light reflex. Changes in the intensity of the environment (general environment or the computer screen in particular) causes pupil to dilate or constrict. This phenomenon is known as the pupillary light reflex (Andreassi, 2006). Simply put, pupil constricts in intense light and it dilates in dim light. Pupil diameter ranges roughly between 1.5 mm and 9 mm. In humans, its reaction to light starts around 0.2 seconds, and peaks between 0.5 and 1.0 seconds (Beatty & Lucero-Wagoner, 2000).

2.2.2. Pupillary response and decision making. Pupillary response is itself a key indicator in decision making. In a very early study, the act of decision making itself was shown to correlate with pupil size. In this study, when two groups of participants were given similar stimuli, a difference in the pupil size occurred with respect to whether the participant makes a decision or not (Simpson & Hale, 1969). In a more recent study, pupil dilation response was found to be a robust indicator of cognitive decision moments; regardless of overt responses, rewards or feedback. Participants' were given a sequence of numbers, each being displayed for 2 s, and were asked to pick one number. Even when they did not give overt responses, their pupils dilate exactly when the number they picked were in display (Einhäuser, Koch, & Carter, Pupil dilation betrays the timing of decisions, 2010). Last but not least, it also shown to be an indicator of cognitive load and attention (Beatty & Lucero-Wagoner, 2000). These studies briefly showed that the moment of decision making was indicated by the change in pupil size.

Pupil dilation response has been also found to be in correlation with rapid fixational eye movements called microsaccades (Rolfs, 2009) in decision making process. In a recent study, researchers found that in a visual search paradigm, participants showed more microsaccades over the chosen item before the decisions (Privitera, Carney, Klein, & Aguilar, 2014). When both responses are taken together, it is further possible to predict decisions beforehand. In a probabilistic selection task (two figures of hidden probabilities of winning are displayed on the screen and participants try to guess the winner) it was found that participants showed more microsaccades over the chosen item and the pupil dilation rate was also higher (Cavanagh, Wiecki, Kochar, & Frank, 2014). It is also an indicator of the direction (shift) of attention. In multiple concurrent and rival stimuli, pupil dilation rates were shown to be indicators of the direction of attention (Kang & Wheatley, 2015; Marx, Gruenhage, Walper, Rutishauser, & Einhäuser, 2015; Marx & Einhäuser, 2015). Changes in perceptual content were also reported to have an effect pupillary response. In a motion induced blindness paradigm, participants' subjective reports of the disappearance and the reappearance of the visual target of the illusion were shown to correlate with their pupillary responses (Kloosterman, et al., 2015).

Neuroimaging studies also showed a strong correlation between pupil dilation responses and locus coeruleus (LC) (Einhäuser, Stout, Koch, & Carter, 2008). LC is the nucleus in the brainstem that produces noradrenaline (NA); a neurotransmitter which is released during shifting attention and decision making (Murphy, O'Connell, O'Sullivan, Robertson, & Balsters, 2014). It also mediates the responses to decisions under uncertainty (Yu & Dayan, 2005; Payzan-LeNestour, Dunne, Bossaerts, & O'Doherty, 2013).

Taken together, these studies showed that pupillary response is an important indicator of the moment of decision making and attention shifts.

2.2.3. Pupillary response, risk taking and emotion. In addition to this extensive body of evidence on the relation between pupillary response and decision making and attention, studies on the relation of pupillary response and risk taking is more recent. Pupillary response correlates with a "surprise" factor, which represents a risky choice combined with an unexpected result. In an experiment, participants were given two consecutive numbers ranging from 1 to 10. After the first numbers given, the participants were asked to decide whether the second number would be greater than the first number or not. When the first number had a low (2-3) or a high value (8-9), and the second number did not satisfy their expectations their pupils dilated more (Preuschoff, Hart, & Einhäuser, 2011; Kloosterman, et al., 2015). More recently, in a decision making task, pupil dilation was shown to increase with expected value. In a simple decision making task, pupil size was shown to be larger when the possible reward of choices were greater (Fiedler & Glöckner, 2012). Interestingly, choosing novel or familiar options also correlates with pupillary response. In another decision making study, pupil sizes were shown to be larger when the decision is novel, rather than it was familiar to (previously encountered by) the participant (Jepma & Nieuwenhuis, 2011).

There is also an accumulated body of research on the relation between pupil dilation and emotional arousal. Studies showed that emotionally arousing stimuli (both pleasant and unpleasant) caused more pupil dilation with respect to neutral stimuli (Partala & Surakka, 2003; Bradley, Miccoli, Escrig, & Lang, 2008). Even in infants, pupillary response was observed against emotionally arousing images. When six month old infants were shown pleasant (happy) faces their pupils dilate more (Geangu, Hauf, Bhardwaj, & Bentz, 2011).

To conclude; the pupillary response is a powerful physiological indicator of decision making, risk taking and surprise. With the assumption that a decision making under uncertainty task depends on emotional engagement, we propose that pupil dilation response must also be an indicator of this engagement, since it was also shown to be an indicator of LC activity, NA production and also emotional arousal. Therefore, in our study, we decided to collect the pupillary responses from participants as a verification of the emotional states.

2.3. Measurement techniques

Measurement techniques of pupillary response were developed along with the eye tracking techniques (Rayner, Pollatsek, Ashby, & Clifton, 2011). The technique used in the TOBII T120 device that was utilized and employed in the present study, is called photo-video oculography (POG-VOG). In this technique, eye movements are recorded and subsequently processed via digital video cameras. This eye tracking method involves da desktop computer with an infrared camera beneath the monitor and special software in it (Figure 4).

In this method, infrared camera gives off infrared light to the eye in order to generate reflections. As the light enters the retina, a large amount of it is reflected back, and creates a bright pupil effect for detection. The corneal reflection is also generated by this infrared light, as a small glint (Figure 5). The importance of this reflection is that its distance to the center of the pupil does not change with respect to head movements,

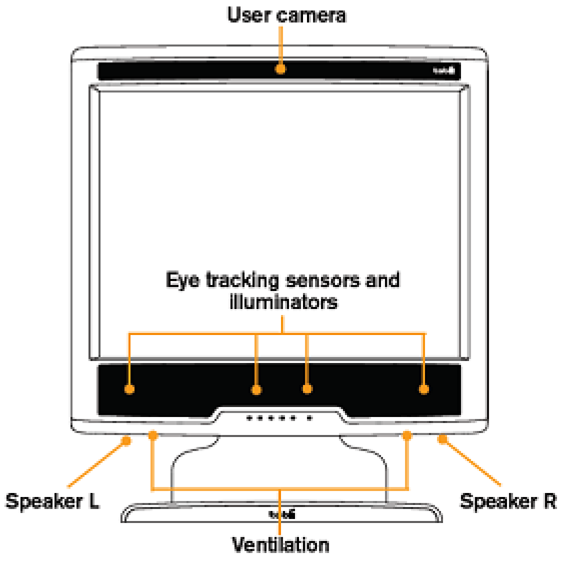


Figure 4: TOBII T120 eye tracker (TOBII T60 & T120 Eye Tracker User Manual 4.0v, 2011).

and therefore providing a robust indicator of the gaze. The eye tracking software recognizes the center of the pupil and this corneal reflection repeatedly and their distance is measured providing the point of fixation. Although it is easy to determine point of regard with corneal reflection only, it is crucial to discriminate eye movements from the head movements. Therefore, the pupil brightness is a key measure in determining point of regard (Duchowski, 2007).

In all video based eye trackers, including pupil/corneal reflection method, a calibration process is required. In the calibration, participants are presented dots at different locations on the screen upon which participants have to fixate repeatedly several times in order to excess a limited threshold. TOBII T120 software development kit provides interfaces and a platform that forces it to be used beforehand.

In addition to measuring fixations and eye movements, eye trackers also have the capability of measuring pupillary responses. While measuring pupillary responses, various methods such as entoptic methods, mirror comparison, scales and callipers, filming, Bellarminow apparatus, Lowenstein pupillograms and infrared photography can be used (see Hakerem (1967) for a complete review of the early pupil measurement history). Latest eye trackers, including TOBII T120, measure pupillary activity by a particular pixel counting method. In this method, by counting the number of pixels in the pupillary area, pupil size is measured. Last but not least, there is also another method to be mentioned, the ellipse-fitting method, where the length of the major axis of an ellipse fitted to the pupil is calculated (Klinger, Kumar, & Hanrahan, 2008).

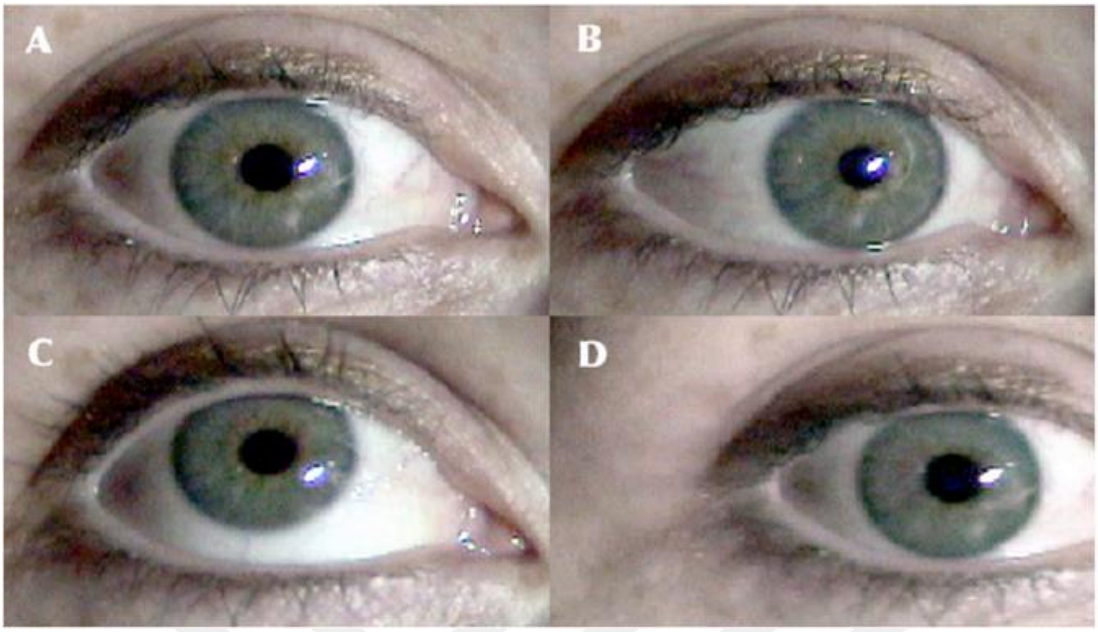


Figure 5: The corneal reflection caused by the infrared light that is being emitted from the eye tracker. Its distance from the center of the pupil gives the direction of the eye gaze.

2.4. Data Processing and Limitations

2.4.1. Reaction time. The primary limitation on the task design in a pupillary response task is the aforementioned reaction time of the pupil. A typical change in pupil diameter is given in Figure 6. Pupil undergoes an initial constriction, mostly due to the change in intensity between consecutive stimuli. Then, shortly before the moment of decision (overt response is not necessary), pupil starts to dilate. After the decision, pupil keeps dilating up to a particular point and then constricts to its original size. Entire reaction takes around 3-6 seconds of time. Therefore, depending on the characteristics of the studied effect, the task is required to contain inter-stimulus intervals (ISI) that reflect this reaction time. Otherwise the data for each response would overlap and data extraction would fail. In our experimental design we eliminated this limitation by locking the screen after participants' actions (button press) for 3 seconds (see Chapter 4 for the details of our approach).

2.4.2. Eye blinks. One of the limitations that occurs while recording pupillary response is due to eye blinks. During eye blinks, pupillary response (as well as the eye gaze) cannot be recorded. This difficulty can be handled by interpolating the missing data or (if necessary) completely removing the pieces of the data in post-processing. In our experiments, we eliminated trials with more than 20% missing data points, and interpolated the remaining missing data points with a 3rd order polynomial interpolator (see Materials and Methods Chapter for details). Figure 7 contains four example

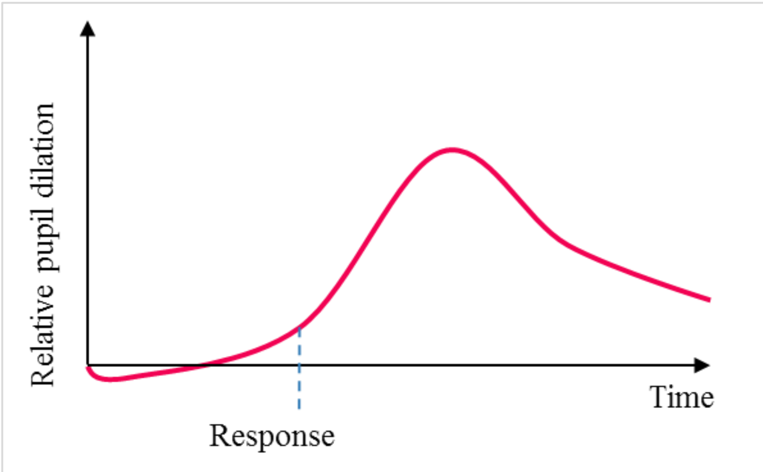


Figure 6: Typical pupillary response in a decision making task. Y-axis represents the relative pupil diameter. X-axis represents the time. Change in the pupil diameter in a decision making task is around 0.5-2 mm, and the reaction time spans between 3-6 seconds.

pupillary responses in the study. Two of these responses contain missing data. Black data points represent these data points and how they were interpolated.

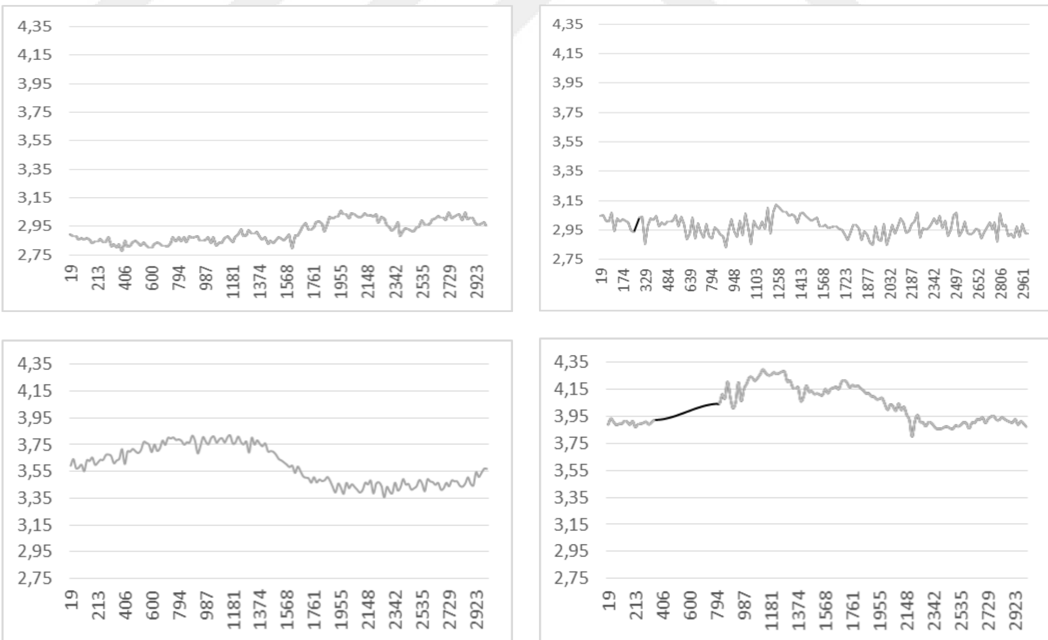


Figure 7: Pupillary responses collected in the study. Four examples are given from four different participants. Y-axes represent pupil size in mm. X-axes represent time in ms. Top-right and bottom-right: There are visible missing data that is interpolated via a third order polynomial (black color). Not all the examples resemble the ideal pupillary response. However, the resemblance becomes evident when several pupillary responses are averaged.

2.4.3. Environment. The sensitivity of the pupil size to light requires a dark and a stable lighting condition in the environment. Therefore, as a rule of thumb, pupillary responses are collected in near-dark environments. As mentioned earlier, pupillary response is sensitive to nearly any kind of cognitive activity. Therefore, the environment is also required to be free of any kind of noise, smell and other stimuli.

2.4.4. Participants. Pupillary response studies demand virtually no requirements from participants. With respect to the technical requirements of the device, participants are seated in front of the computer screen with a particular distance (in TOBII T120, it was 60-100 cm). In mobile devices this issue is also irrelevant. For some devices, glasses may be an issue and a prerequisite for the participants. In TOBII T120, we did not encounter a problem regarding to this issue.

2.4.5. Calibration failures. There are also cases when the device fails in the calibration step and fails to provide any data at all. In our studies, this particular problem was handled by placing a notification bar to the experiment interface. This notification bar made a real-time calculation of the percentage of the available data points and displayed this information. If the percentage is extremely low (i.e. less than %10) the administrator of the experiment aborted and restarted the experiment (details of our approach will be provided in the task design).

2.5. Summary

As summarized in this chapter, pupillary response is now being used commonly in several fields of cognitive research, including decision making. Despite its limitations, it posits several beneficial aspects: Compared to fMRI, participants are not required to be placed in a machine with a strict set of procedures. Compared to fNIRS or EEG, the participants are not required to wear any sorts of equipment. As of now, the developing eye-tracker technologies provide more mobility and less dependence on the environment; making the pupillary response even more available for scientific research.

As mentioned before, the present study propose that risk taking behavior in a sequential decision making task depended on the participants' previous responses and their outcomes. In order to verify this dependence in the modality of a physiological response, we decided to collect and analyze the pupillary response. As a result of its close relation to decision making, arousal (Partala & Surakka, 2003; Bradley, Miccoli, Escrig, & Lang, 2008), risk taking (Preuschoff, Hart, & Einhäuser, 2011; Jepma & Nieuwenhuis, 2011; Fiedler & Glöckner, 2012); and its accessibility and usability, we decided to collect pupillary responses from our participants.

CHAPTER 3

LITERATURE REVIEW

3.1. Decision Making – History and Background

Early decision making research focused on the uncertainties and ambiguities, changes in reward/punishment amounts and changes in win/lose probabilities in hypothetical gambling situations (see Camerer (1999); Camerer & Loewenstein (2004); Wu, Zhang & Gonzalez (2005) for reviews). These studies aimed to find mathematical formalizations of rational decision making. Research on the individual differences and emotional aspects of decision making were addressed relatively later, partially in accordance to the emergence of neurobiological imaging techniques and capabilities. We refer the former group of studies as the behavioral economics and the latter group as neuroeconomics.

3.1.1. Behavioral economics. Behavioral economics studies the rationality of individuals, who were encountered with economic decisions (Camerer C. , 1999). One of the simplest method to predict decisions among a set of probabilistic win-lose choices is the calculation of their expected values (EV). It is the value of the outcome, multiplied by its probability. For instance, a gamble that gives $100 with a probability of %5 has an EV of $100 * 0.05 = $5.

Nearly three centuries ago, Bernoulli introduced the term expected utility, to account for particular cases that the EV calculation failed to explain, such as marginal values (Bernoulli, 1954). Consider the choice between two alternatives: the first alternative is the previously explained gamble (EV = $5) and the second alternative is to receive an immediate $4 (EV = $4). Bernoulli observed that although the EV of the first alternative is greater, people preferred the second alternative more frequently. He claimed that the EV must be corrected by a function to account for such marginal probabilities and outcomes. Significance of his work was that it was the first attempt of formalizing decision making; the first milestone in this domain of research (for a review; see Baron (2005)).

Decision maker in the expected utility theory was always assumed to be rational (for an axiomatization; see von Neumann, Morgenstern, Kuhn, & Rubinstein (2007)). However, human behavior is complex, and the precision of these approaches were rather low when predicting it. In particular experimental setups, risk taking and risk aversion behaviors caused non-optimal decisions (participants persistently made non-optimal decisions). Moreover, in some situations there appeared to be persistent patterns of behavior such that the alternative choices had the exact same probabilities (even when the alternative option had the exact same probability of winning, participants did not choose that alternative).

In the attempts of explaining such human decision making behavior, objective (or rational) expectation based models were gradually developed into more subjective models (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Wakker & Fennema, 1997; Caplin & Dean, 2009). The aim of these models was to explain the human factors in decision making. In one of their earliest experiments Tversky and Kahneman (1979) provided an example of a decision scenario for one of these persistent patterns: Participants were given a decision on two alternatives. First alternative was winning an instant reward of $1. Second alternative was joining a bet with a reward of $2 with %50 probability (they would either win $2 or win nothing). In a complementary decision problem, they reversed the situation: First alternative was losing an instant $1 and the second was the gamble of losing $2. They observed opposite behaviors in two scenarios (Kahneman & Tversky, 1979). Although the two situations were mathematically identical, participants preferred the risky gamble in the first situation, whereas they preferred the certain loss (instead of taking the risk of losing $2) in the second – a phenomenon that they called as the loss aversion.

Kahneman and Tversky (1979) also found that human decision making was not only a result of expectations, but a result of subjective evaluations of those expectations. In other words, rather than the absolute values of the outcomes, their perceived values were important. They showed that two gambling situations with similar probabilities but different amounts of outcomes were perceived differently. Consider two decisions. The first one is between an instant reward of $1 and a bet of winning $100 with %1 probability. The second is between $100 of instant reward and a bet of winning $10000 with again %1 probability. Participants were shown to prefer the second alternative in the first decision (they risk for the greater reward) but the first alternative in the second decision (they are satisfied with the $100). The authors claimed that when reward/punishment amounts were extremely high, participants' sensitivity started diminishing.

Their observations led them to their Prospect Theory, which stated that people made decisions based on the subjective potential values of gains and losses (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Wakker & Fennema, 1997; Wakker, 2010). Basically, they invented more complex utility functions to account for the patterns of human decision behavior that they observed. To summarize, as a major improvement on previous expectation based models, their approach proved to be more descriptive on decision making problems in experimental settings.

However, there were still more complex examples that were presented to the field of behavioral economics (for two famous paradoxes; see (Allais, 1953; Ellsberg, 1961)). These were examples to hypothetical choice problems where the participants' decisions were actually non-optimal yet more risk aversive. In the Ellsberg paradox for instance, participants were given two decisions regarding an urn that contains 90 balls: 30 red, and 60 black/yellow. Exact number of black and yellow balls were unknown.

First decision:

- (Decision A) win $100 if you pick a red ball.
- (Decision B) win $100 if you pick a black ball.

Second decision:

- (Decision C) win $100 if you pick a red or a yellow ball.
- (Decision D) win $100 if you pick a black or a yellow ball.

A simple pre-analysis would suggest that if the participant chooses A, it implies that she believes that there are more yellow balls than black balls. This means that she would then choose C.

Although being contradictory, participants were observed to pick decisions A and D. Relevance of this paradox to our context is that it pointed out more complex patterns of human behavior that determined decision making: their values, assumptions and characters were in play. In this example, Ellsberg (1961) stated that people had a tendency to avoid ambiguity. They preferred "the devil they know", when probabilities and utilities were not available or hard to evaluate.

Paradoxes such as Ellsberg Paradox arise because of the deviation of the human behavior from the rational decision maker of behavioral economics. But to summarize, there is a historical significance of behavioral economics in the context of this thesis that comes from its efforts to model the rational behavior in a variety of decision making scenarios; therefore providing a foundation to decision making studies in cognitive science.

Neuroeconomics began as, and still is, the program of cognitive and neurobiological imaging studies to test and to figure out the underlying neural structures of the questions and the theories that have been presented by behavioral economics (Rustichini, 2009).

3.1.2. Neuroeconomics. Investigation of individual differences and emotional aspects of decision making started relatively later than behavioral economics, and mostly in parallel with the development of neurobiological imaging techniques. Neuroeconomics, basically, is the study towards an understanding of neurobiological functions under decision making. Studies in neuroeconomics basically aim to provide insights on decision making behavior by determining underlying physiological and brain structures and by explaining the behavior over individual differences (Zak, 2004; Glimcher & Rustichini, 2004; Loewenstein, Rick, & Cohen, 2008; Rustichini, 2009).

By investigating classical concepts and theories from behavioral economics (Ellsberg paradox for instance (Hsu, Bhatt, Adolphs, Tranel, & Camerer, 2005; Huettel, Stowe, Gordon, Warner, & Platt, 2006)) and through the use of tools that can access neural and physiological responses, studies in neuroeconomics aim to accomplish mathematically and biologically plausible models of human behavior. They extend the decision making paradigms of behavioral economics by checking the biological validity of that model and aiming to improve its accuracy by making use of the neurophysiological data. For instance, in one of the earlier studies in neuroeconomics, the aforementioned Prospect Theory was employed in a neuroimaging experiment (Breiter, Aharon, Kahneman, Dale, & Shizgal, 2001). Researchers reported brain activation in similar brain areas on subjective potential values (of Prospect Theory) in the given task.

There are a variety of methods used in neuroscience to study neurophysiological activity, and each one has its own advantages and drawbacks such as their spatio-temporal resolutions, limitations of the experimental setup or practical considerations regarding participants. The list comprises of a vast number of methods including brain imaging techniques (fMRI, PET), electro-physiologic recordings (fNIRS, EEG, pupil dilation, SCR, etc.), brain stimulation (rTMS) and lesion studies (Ruff & Huettel, 2013) (see also Section 3.2 for a brief list).

To summarize, neuroeconomics assumes that more realistic models of human decision making will lead to more accurate prediction of economic choice. Although being a relatively new area of research, neuroeconomics has already significantly contributed immensely to the knowledge in decision making (Glimcher & Fehr, 2013).

3.2. Neuroimaging Studies in Decision Making

Converging results of the studies in neuroeconomics indicate that rather than being rational, individuals are in particular emotional decision makers (see Loewenstein & Lerner (2003); Sanfey & Chang (2008); Phelps, Lempert, & Sokol-Hessner (2014); Lerner, Li, Valdesolo, & Kassam (2015) for reviews). In a more general perspective; stress (Lighthall, et al., 2012), mood (Harlé, Chang, van 't Wout, & Sanfey, 2012), social environment (Moretto, Làdavas, Mattioli, & di Pellegrino, 2010) can also be added to the list of emotional factors that play role in decision making.

In the particular case of decision making under uncertainty, emotional aspects are commonly studied by parameterizing reward/punishment amounts, win/loss probabilities or (providing / not providing) immediate feedback; therefore triggering arousal. Such research reveals a structural network consisting of dorsolateral prefrontal cortices (DLPFC – executive centers of human brain) and several areas related to different aspects of emotions: ventromedial prefrontal cortices (VMPFC) that acts as a relaying mechanism of emotional triggers, orbitofrontal cortices (OFC) that plays a major role on reward-punishment feedback, insula, anterior cingulate (ACC) and basal ganglia (amygdala, nucleus accumbens (NAcc)) that are mainly responsible for coding and processing of emotion (for reviews see Gupta, Koscik, Bechara, & Tranel (2011); Schonberg, Fox, & Poldrack (2011)). A list of studies in this field is given in Table 2.

To conclude, these studies indicate that decision making under uncertainty is the result of an interplay between executive centers and emotional centers of the brain. This implication summarizes the significance of this brief summary; that these studies altogether help constitute a program of discovering the neural underpinnings of the effect of emotions on decision making.

3.3. Decision Making Tasks – An Overview

3.3.1. Balloon Analog Risk Task (BART). BART is a decision making task that is developed as a measure of risk taking behavior (Lejuez, et al., 2002). In the original BART, there is one single balloon on the visual interface (Figure 8). There are two options for the participant. She can pump the balloon by pressing a button, causing some points to be accumulated. However, these points are temporary. She can also choose to collect the accumulated points of the balloon to a permanent cache by pressing another button. The collected balloon is replaced with a new deflated one. But every now and then the balloon pops, causing all temporary accumulated points in the balloon to be lost.

The aim of the task is to store as much points as possible in the permanent cache. Total number of (popped / collected) balloons is fixed (it is 90 in the original work).

The relevance of BART in the context of our study comes from its method. Learning the balloon popping probabilities and optimal decision patterns in BART proves to be a difficult task, preventing participants to develop decision making strategies. It is an emotionally engaging task with win-loss responses immediately given after participants' actions (also accompanied with a popping sound). There is also the apparent emotional aspect of pumping a balloon with a probability to pop. Furthermore, it is also correlated with natural risk-taking attitudes (Lejuez, et al., 2002). With these capabilities, BART proves to be suitable paradigm to analyze the temporal aspects of decision making under uncertainty.

Authors of the original BART task reviewed their works and discussions on methodological considerations of the task in a website (http://www.impulsivity.org/measurement/BART). These analyses include test-retest characteristics (White, Lejuez, & de Wit, 2008), extensions to different age groups (Lejuez, Aklin, Zvolensky, & Pedulla, 2003) and its neural correlates (Rao, Korczykowski, Pluta, Hoang, & Detre, 2008).

Table 2: A Selection of Studies on Decision Making Under Uncertainty. All together, these studies implicate a complex neural network, spanning areas responsible for executive functions, reward prediction and emotions.

Study	**Task**	**Results**
(Rogers, et al., 1999)	Cambridge Gambling Task (CGT)	Lateral OFC and ACC responds to low probability – high reward choices against high probability – low reward choices.
(Critchley, Mathias, & Dolan, 2001)	*no name*	Lateral OFC, ACC and insula respond to different levels of risk.
(Kuhnen & Knutson, 2005)	Behavioral Investment Allocation Strategy (BIAS)	Gain prediction in NAcc, Loss prediction in anterior insula.
(Tobler, Christopoulos, O'Doherty, Dolan, & Schultz, 2009)	*no name*	OFC activation in risk aversive group.
(Rao, Korczykowski, Pluta, Hoang, & Detre, 2008)	Balloon Analog Risk Task (BART)	DLPFC and ACC activation in voluntary decisions.
(Weller, Levin, Shiv, & Bechara, 2007)	Cups Task	DMPFC activation in risk aversive group. VMPFC responds to the magnitude of reward.
(Knoch, et al., 2006)	CGT	DLPFC as an inhibitory control against “seductive” immediate payoffs.
(Fecteau, et al., 2007)	CGT	DLPFC as an inhibitory control against risk taking; helping a manifestation of risk aversion behavior.
(Bechara, 2004)	Iowa Gambling Task (IGT)	Amygdala, OFC and VMPFC controls emotional responses to immediate outcomes.
(Morris, Nevet, Arkadir, Vaadia, & Bergman, 2006)	Bandit Task	Basal ganglia predict and handle rewards and punishments.

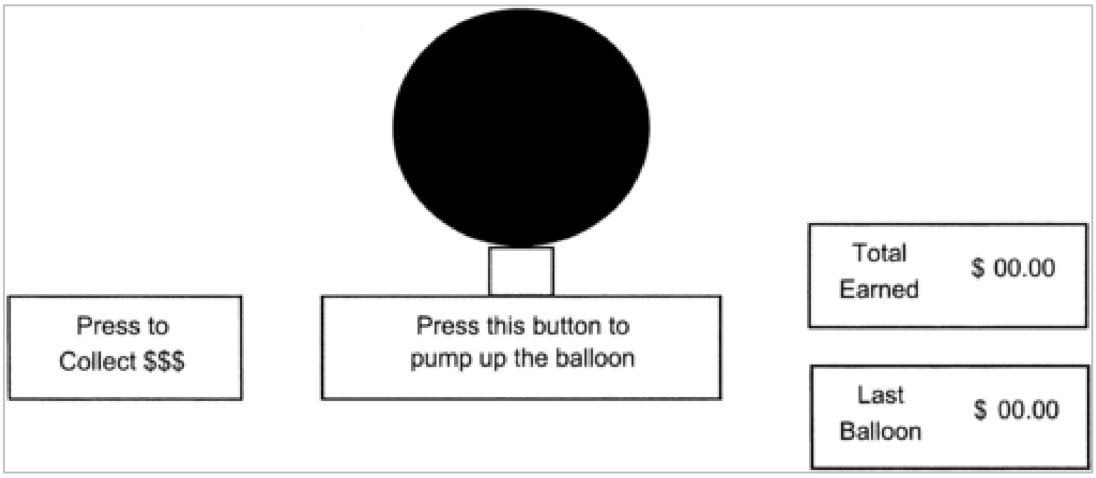


Figure 8: Graphical user interface of BART (Lejuez, et al., 2002). Participants press the particular button on the screen to pump or collect the reward. They can follow the amount of reward on the current balloon, as well as the amount of total collected reward. The size of the balloon changes according to pumps and pops.

3.3.2. Iowa Gambling Task (IGT). Iowa Gambling Task has been designed in order to investigate the role of emotions in decision making. It has been a milestone for the studies of emotional underpinnings of decision making (Bechara, Damasio, Damasio, & Anderson, 1994; Damasio, Everitt, & Bishop, 1996; Bechara, 2004; Bechara & Damasio, 2005; Reimann & Bechara, 2010; Gupta, Koscik, Bechara, & Tranel, 2011). Results of the IGT led these researchers to the Somatic Marker Hypothesis (SMH) that was a neurobiological model of decision making with respect to the effects of emotions.

SMH (Damasio, Everitt, & Bishop, 1996) principally focuses on emotional aspects of the process. The hypothesis posits that body (somatic) states, which are driven by

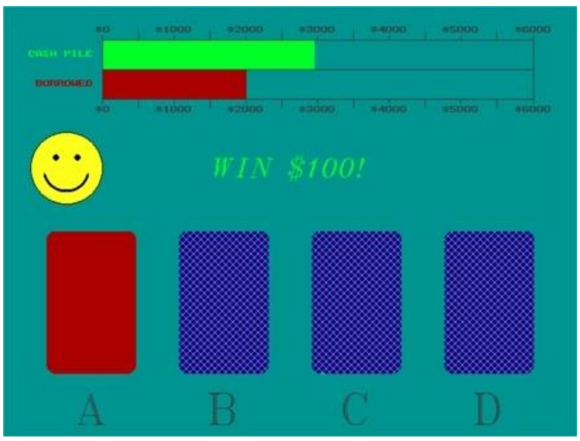


Figure 9: Screenshot from the original Iowa Gambling Task. Total reward and punishment amounts are given at top. An immediate feedback is given with a text and a smiley figure, if there is a reward.

affective cues and emotional states, act as markers to trigger particular risk attitudes in decision making. The idea behind the hypothesis originated from IGT, which is in principle a card gambling task (Figure 9). IGT (Bechara, Damasio, Damasio, & Anderson, 1994) consists of turning cards sequentially from one of four decks of cards (A to D). Each card causes either a certain gain or loss. Cards from decks A and B yields higher and equal gains than from decks C and D. All decks contain penalty cards with certain frequencies (more frequent in A and C, with respect to B and D), causing players to lose certain amounts of savings. In the long run, first two decks cause same amount of loss (disadvantageous decks) and on the other hand, decks C and D cause the same amount of gain (advantageous decks). Participants are given a certain amount of credits and instructed to sequentially turn cards from any deck they choose, until being told to stop. Gain-loss frequencies of decks are 10 cards, and the task is stopped after the 100th step. The fundamental aspect of the task is the implicit learning of the decision behavior. Namely, a shift occurs from the decisions with a more immediate reward (that result in a future punishment) to decisions with a future reward.

Damasio and Bechara investigated performances of three groups, consisting of healthy controls (control 1), patients with damage to either lateral OFC or lateral temporal cortices (control 2) and patients with damage to VMPFC (experimental group) in this task. Their findings showed that both control groups gradually but consistently move from disadvantageous to advantageous decks and permanently stay that way until the end of the task. However, patients in the experimental group preferred disadvantageous decks over others, in contrast with the controls. With intervals of 10 cards, the task was paused and players are questioned for explicit knowledge of the probabilistic nature of the task, yet it was observed that no such knowledge emerged during the task.

What makes these results intriguing, partly arise from the fact that VMPFC patients have superior memory and IQ. In a Wisconsin Card Sorting Task (WCST), they were furthermore shown to handle response inhibition well (Anderson, Damasio, Jones, & Tranel, 1991). The most apparent diagnostic on these patients may be on their social behaviors, such as obstinacy, and impatience on their desires, devising yet immediately abandoning future plans (see Macmillan (2000) for the famous case of Phineas Gage). During the task, participants’ skin conductance responses (SCR) are also investigated. Key finding of this investigation was that in the course of the task, in healthy participants, a detectable SCR response is developed prior to card selection; and it is higher in magnitude for disadvantageous decks. However, this response (i.e. somatic marker) is absent in VMPFC patients. Damasio and Bechara therefore hypothesized that decision making under uncertainty and risky conditions is at least partially affected by emotional cues; and these cues are processed/controlled mainly by VMPFC. These cues can be actual bodily signals; such as changes in heart rate or blood pressure, as well as “images” of previous emotional states. Role of VMPFC in this scenario is to be responsible for relaying these states with behavior, and to learn these associations. Learning can be implicit; therefore the individual may well be unaware of these cues at all (for objections and discussions on SMH see Maia & McClelland (2004); Bechara & Damasio (2005); Maia & McClelland (2005); Lin, Chiu, Lee & Hsieh (2007); Chiu, et al (2008)). We will shortly refer to this discussion in the Future Work and Implications section.

3.3.3. Cambridge Gambling Task (CGT). This task is initially designed to determine the individual differences in neural correlates of EV (expected value) in a decision making task (Rogers, et al., 1999). An array of boxes is displayed in a computer screen, each box made of one of two different colors. Participants are instructed to select one of the two colors to win. Amount of monetary gain and loss is negatively correlated and winning probabilities are positively correlated with the percentage of that color (Figure 10). These parameters are provided to the participant, and they are fairly easy to calculate. Therefore, it is an example of decision making tasks that participants can develop winning strategies during the trials. Another significance of CGT is that it contrasts directly with the neural substrates of large risks and safe decisions.

3.3.4. Columbia Card Task (CCT). The task is developed in an attempt to distinguish two primary aspects of decision making; namely, affective and deliberative components (Figner, MacKinlay, Wilkening, & Weber, 2009; Panno, Lauriola, & Figner, 2013). The task has two alternative versions. In the “hot” version, 32 cards are shown face down on a computer screen. Among them are gain and loss cards. Number of loss cards, gain and loss amounts are given to the participants. Participants turn over cards one by one until they voluntarily stop or hit a loss card. “Cold” version differs in the sense that participants are required to choose the number of cards to be turned over, before the task. They are not allowed to interfere further, until (maximally) that number of cards are turned over randomly (Figure 11). The most important aspect of this design is the decomposition of cognitive/deliberative motives and affective influences of risk taking. Moreover, it does not involve a learning component. When these two versions in different age groups were investigated, it was found that adolescents showed greater risk taking behavior in the hot version compared to the cold one.

Figure 10: Cambridge Gambling Task. One of the six boxes contains the reward with a probability of 1/6. Participant picks one of the two colors. If she picks the correct color she receives a reward that matches the color.

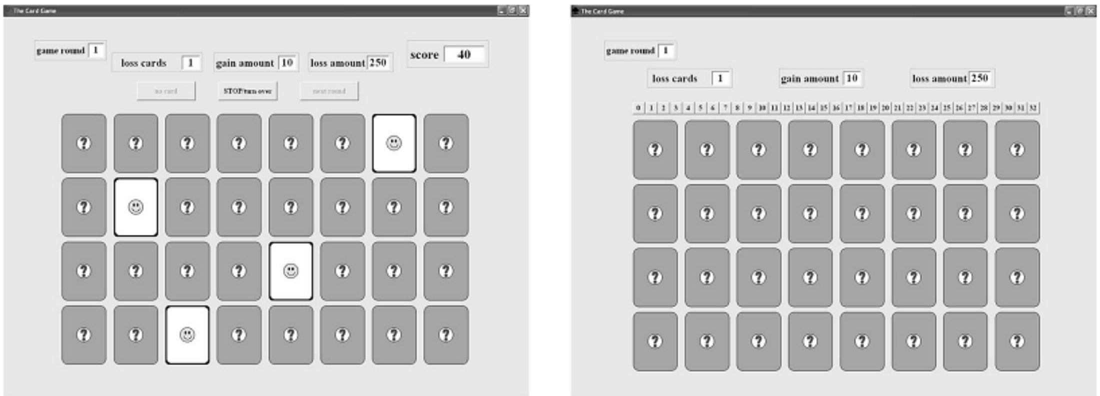


Figure 11: Columbia Card Task. Left panel is the hot case, and the right panel is the cold case.

CCT can be considered as a more adaptable and functional derivation of BART. From the CCT perspective, one can consider BART as a simplification of CCT that comprises of only a hot version.

3.3.5. Cups Task. In the Cups Task (Weller, Levin, Shiv, & Bechara, 2007), participants are asked to choose between a risky and a safe option. Risky option consists of two, three or five cups. One of the cups contains a monetary reward, and the others are empty. Safe option is a guaranteed gain, but of a smaller reward. Essence of the task is that by manipulating the amount of gains, it becomes possible to distinguish whether the risky option is favorable or not.

3.4. Summary

In general, tasks that are used in studies of neuroeconomics parametrize win/lose probabilities and reward/punishment amounts and utilize the risk in order to reveal individual differences by observing and analyzing neurobiological and behavioral responses. In this chapter, a small subset of decision making tasks is given, along with their contributions to neuroeconomics.

The neuroimaging studies that utilize these tasks show that decision making under uncertainty differs among individuals with respect to their risk taking characteristics. It is an interplay between executive and emotional centers of the brain.

An issue that has been neglected in these studies is the temporal progression of human behavior in risk taking tasks. More specifically, one question remains unanswered: what kind of an emotional change do the participants undergo when they receive a positive outcome, or a negative outcome? Aforementioned studies are more interested in the average behavior of the participants, rather than an answer to this question. In this sense, they assume that the individuals behave similarly throughout an experiment (excluding learning and strategy developing): regardless of what outcomes they get, their emotional states do not change.

To uncover the kind of an emotional change the participants undergo when they receive a positive outcome, or a negative outcome, we performed a series of experiments. In two main experiments, we employed a modified version of BART (details of the modification will be provided in the following chapter). We preferred BART mainly because learning a winning strategy is difficult and because it is an emotionally engaging task. We also employed CGT and Cups Task in two follow-up experiments to check for a generalization of some of the results obtained in these experiments.

Neuroeconomics tells us that decision making under uncertainty depends on individual differences. But do the individuals stay the same or do they change behavior during the course of the experiments, is a wonder. We will try to answer this question throughout the studies designed in this thesis.

CHAPTER 4

METHOD AND EXPERIMENT

To recall, our research questions include whether the previous decisions and their outcomes (in a decision making task) effect the current decision. To understand and formalize our hypotheses we propose a novel sequential decision making task that allows us investigate the risk taking behavior based on previous decisions and outcomes. In order to achieve this novel task, we modified the BART to achieve our requirements.

This chapter begins with introduction to this novel task. Following this introduction, a list of the studies that were employed are given in detail.

4.1. Modified BART: m-BART

Our choice of BART in testing our hypotheses was in general due to its two aforementioned characteristics: Strategy developing in BART is very hard and it is emotionally engaging.

However; one particular aspect of the task, the inflation step, poses a problem to our purpose. In BART, when the balloon pops, participants have no other option but to restart over with a new deflated balloon. The dynamic aspect of the task is interrupted in such a situation. Whether they regret their decision or not, the immediate response after the last balloon pop should always be to pump; since there is no other choice (the new balloon is completely deflated, all accumulated points until that point are lost, and there is nothing to collect). In order to understand whether the previous decisions and their outcomes effect the current decision, the decision that comes after a balloon pop is an essential moment to be investigated.

We modified BART in order to remove the aforementioned interruption. Our modified version, m-BART works as follows: Participants are given multiple balloons (with number N), placed horizontally in a similar computerized environment with the original task. There are two options to choose from:

- Pump all balloons at the same time
- Collect the reward of a single balloon

There is apparently no need for a button to collect all at the same time; participants can always do that one by one. Balloons inflate/pop with different probabilities than the original task. These probabilities were fine-tuned and adjusted after a preliminary study that will be introduced in this chapter. A balloon that pops is replaced with a new and deflated one immediately. More than one balloon can pop at the same time.

Participants have a particular sum of initial balloons. Similar to BART, a balloon pop removes 1 balloon from the stack. Collecting the reward in a balloon has the same result. Figure 12 illustrates the graphical user interface (GUI) of the m-BART.

The key point of our modification is that the experiment does not get interrupted by any type of outcome, allowing us to fully examine the temporal dynamics of the task.

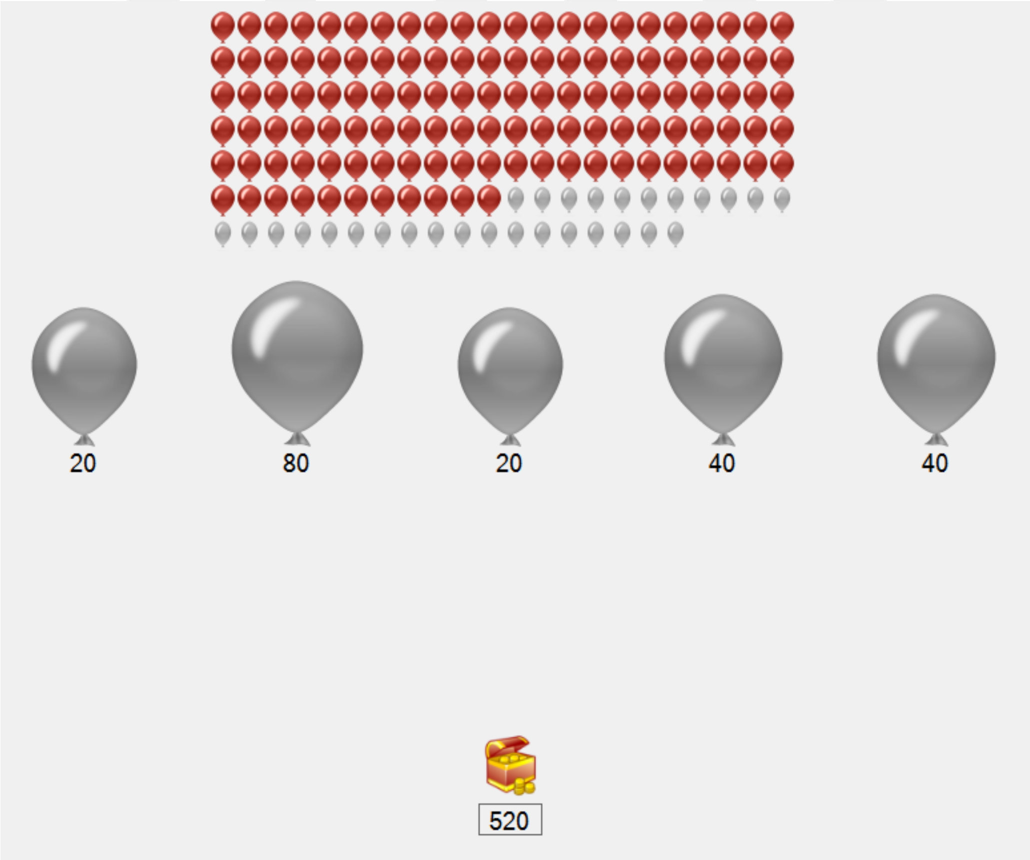


Figure 12: Screenshot from m-BART. Numeric values under balloons represent how much the balloon is inflated and the reward to be gained if the reward of the balloon is collected (sum: 200). Treasure box indicates overall collected reward from the beginning of the experiment. Top row indicates experiment timing in terms of popped and collected balloons. Choice of 5 balloons is arbitrary, though more balloons would posit problems in using the keyboard and keeping the necessary eye contact when collecting pupillary response.

As in the same example before, when a balloon or a number balloons pop, there are still other balloons remaining, allowing participants to decide to continue pumping or collecting them.

To notice; even with multiple balloons, there can still be situations where all balloons pop together and leave participant again with no choice but to pump. The probability of such an event to occur is very low (with our choice of 5 balloons). We nevertheless checked the experimental data after the experiments and ensured that it had not happened during the experiments.

As a side note; CCT, which is also a suitable task to test our hypotheses, was not chosen in our study simply because of its usability issues that would otherwise have a negative impact to pupillary response collecting. User interaction in BART proved to be simpler and more appropriate for this kind of a task. More of this discussion on the choice of BART will be given later in discussion chapter.

4.2. Overview of the Studies

A series of experiments were executed and one simulation was run to test particular aspects of the hypotheses. A complete list is given in Table 3.

The aim of **the preliminary experiment** was to verify the m-BART. It was an exploratory experiment where both the experimental parameters and the application as a software graphical user interface were tested.

Experiment 1 is the main experiment of the thesis. M-BART was executed while pupillary response is collected from participants.

Experiment 2 is a replication of Experiment 1, only without the pupillary response. Aim of this experiment was to analyze response times of participants without the limitations of the pupillary response setup.

The simulation was developed and run in order to compare participants' performances to a simple agent. A simple algorithm was developed and the m-BART was run for this purpose.

Finally, **two supplementary experiments** were executed; one by Cups Task and one by CGT. The aim of these two experiments was to check whether our assumptions generalize to these tasks in addition to m-BART.

Table 3: Complete list of the studies in the thesis. "✓" signs denote the existence and "X" signs denote the absence of that feature.

	Task	Participants	Pupillary Response	DOSPERT Survey
Preliminary Experiment	m-BART	55	X	✓
Experiment 1	m-BART	22	✓	✓
Experiment 2	m-BART	12	X	✓
Simulation	m-BART	-	-	-
Suppl. Experiment 1	Cups Task	12	X	X
Suppl. Experiment 2	CGT	11	X	X

4.3. Preliminary Experiment and Fine-Tuning of the Task

Although BART is a commonly used task in neuroeconomics and m-BART is derived from it, m-BART is a novel task. Before starting with the actual experimental procedure, it was essential to test m-BART on a set of participants in an easily accessible setting. Therefore an exploratory experiment was run. The aim of this experiment was to adjust experimental parameters and to verify that the modification works.

To serve this purpose, a web application was developed that can be accessible via any computer having a modern Internet browser, and tablet PC's as well (Figure 13).

4.3.1. Participants. 55 subjects participated. All participants completed the task in their own, personal environments. No biographical information was collected.

4.3.2. Procedure. Participants completed the m-BART with 5 balloons. No pupil dilation response collected and no monetary reward was given.

Participants were given two different options to pump balloons. One option is to pump a single balloon. There were five pump buttons to match the number of balloons. The other option is to pump all balloons at once. When this button was pressed, all balloons were attempted to be pumped independently. However, this was the risky option: the popping probability and the gain modifier were two times than the first option.

Target variables were randomly assigned in the beginning of the experiment by the software. The set of popping probabilities were %20, %25, %35 and the set of gain modifiers were 1.5, 2, and 2.5. The risky button was assigned with the double popping probability and double gain modifier in each case.

4.3.3. Results. Results of the preliminary experiment contributed to m-BART in two aspects:

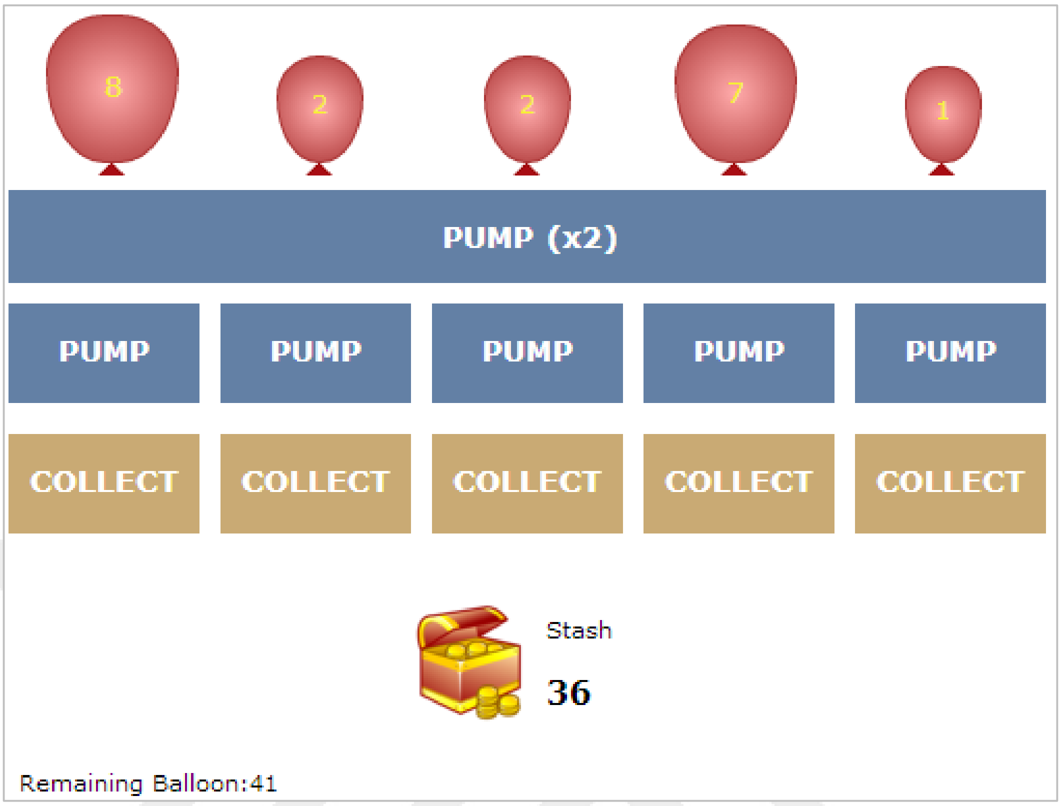


Figure 13: Screenshot from the preliminary experiment

- Task and the software was tested and verified.
- Popping probabilities and gain modifiers were adjusted.
- Individual balloon pumping buttons were removed.

An exploration of participants' pump and collect counts was done to specify these parameters in order to avoid participants to develop winning strategies in the experiment to follow.

The second finding from this study was related to the separate pumping buttons for each balloons. Our original assumption was that when participants are in a risk taking state, they would prefer to pump all balloons at once (because it would pump them with a greater gain modifier). Therefore by monitoring this button the risk states could be distinguished. Analysis of the preliminary results showed that the majority of the participants were confused with these options and chose to continue with the individual pumping options. Majority of the participants tended to execute the task with only one balloon, ignoring the other buttons. Then however, the modified task became analogous to the original BART.

4.3.4. Final setting. In the final setting, we assigned 1 button to pump all balloons at once, and separate buttons for each balloon to collect accumulated rewards. Unneeded buttons were removed from the special numpad (Figure 16). The gain modifier was 2. Balloons started with a reward of 10 (an initial value that was simply greater than zero). In each successful pump, it was multiplied with 2. The popping probability was specified as %25. In an exploration of the results of the preliminary experiment (not reported here) we observed that with a smaller gain modifier or a higher popping probability, participants preferred not to pump. On the other hand, in the opposite situation, they preferred pumping the balloons indefinitely.

The screenshot of the final setting is as given in Figure 12. The number of total balloons that the participants can pop/collect was specified as 150. In the original study of BART, this was specified as 90. Our choice of increasing this number was to gain more insight on the task as a sequence. In our own tests, in the preliminary study and (as will be given later) in the actual experiment we observed that the entire m-BART task (not the whole experimental session) took 10-15 minutes with 150 balloons. We also did not get a negative feedback from the participants concerning the length of the task. On the contrary, some of the participants explained their thoughts that the task was very engaging and perceived as short.

In contrast to the original study, we gave the number of remaining balloons in the interface as small red balloons at the top, in order for participants to know about the progression of the task. After balloons popped or collected, these balloons turned gray. Its effects on the change of intensity were checked (given in the results chapter). However, the condition where there was no such indication was not checked.

In m-BART we also simplified the popping probability with respect to the original BART. In the original BART, a balloon can hypothetically be pumped 128 times at maximum. Popping probability was gradually increasing such that at the n^{th} pump it was n/128. The aim of this simplification was to prevent participants to gain any kind of knowledge about the rules of the task. In our analyses we saw that this setting did not cause any major change in behavior throughout the task (pumping more or less towards the end of the task). Further details of the analysis is provided in the results chapter.

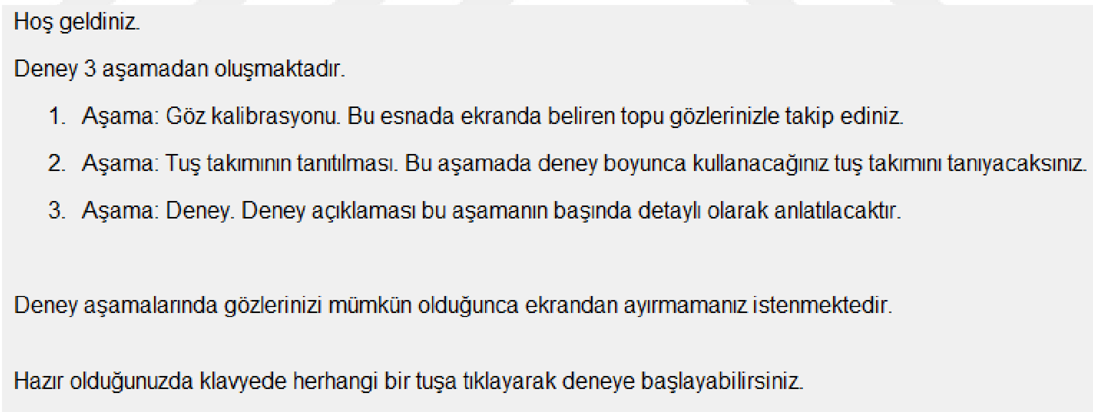
4.4. Experiment 1

4.4.1. Participants. 22 subjects (10M, 12F, age range = 23 to 36 years, mean = 29.3, stdev = 3.9) participated. All participants were university students or graduates from Middle East Technical University. Participants were given the DOSPERT (Domain specific risk attitude scale) survey prior to the m-BART, which was priorly translated to their native languages (Turkish). The original and the translated versions are provided in Appendix A. The translation was not validated through a norm study. DOSPERT was given in order to elaborate on participants' risk taking attitudes and their m-BART results. All participants gave written consent to participate.

4.4.2. Procedure. Upon completion of the DOSPERT survey, a general instruction screen about the task was given[3] (Figure 14). An eye gaze calibration screen was shown after the instructions that is required by the eye tracker (Figure 15). This was followed by the original BART with 1 balloon to conduct training and practice. Finally, 5-balloon m-BART was given. The entire session took 20-25 minutes on average. Only the data from the 5-balloon m-BART were analyzed.

All experiments were held in a near dark environment provided in the eye tracking laboratory. Pupillary data was collected via a TOBII T120 eye tracker, providing a data rate of 120 Hz. Participants were seated across the monitor with a distance of approximately 60-100 centimeters.

A special keyboard was developed for the task. A regular numeric keypad was taken and all keys except '/', '8', '5', '2', '00', '6' were removed. Empty key areas were covered with solid plastic. Remaining keys match the pumping-collecting pattern on the task screen (Figure 16). Regarding this keyboard (numpad), no negative usage was reported at the end of the experiment. Participants were also given a warm-up screen before the experiment. All participants were observed to control the keyboard without difficulty and without looking at it[4] (Figure 17). All participants had a minimum of 86 percent of eye contact during the 5-balloon m-BART. No monetary reward was given at the end of the experiment.


Hoş geldiniz.

Deney 3 aşamadan oluşmaktadır.

1. Aşama: Göz kalibrasyonu. Bu esnada ekranda beliren topu gözlerinizle takip ediniz.
2. Aşama: Tuş takımının tanıtılması. Bu aşamada deney boyunca kullanacağınız tuş takımını tanıyacaksınız.
3. Aşama: Deney. Deney açıklaması bu aşamanın başında detaylı olarak anlatılacaktır.

Deney aşamalarında gözlerinizi mümkün olduğunca ekrandan ayırmamanız istenmektedir.

Hazır olduğunuzda klavyede herhangi bir tuşa tıklayarak deneye başlayabilirsiniz.

Figure 14: Instructions screen of experiment. Text is given in participants' native language, Turkish.

[3] The English translation is as follows: "Welcome. The experiment comprises of 3 steps. First step: Eye calibration. In this step, please follow the ball that appears on the screen with your eyes. Second step: Keyboard warm-up. You will be introduced to the keyboard that will be used in the experiment. Third step: Experiment. A detailed experiment introduction will be given beforehand. Please keep your eyes on the screen as much as you can. When ready, please press any button on the keyboard to start."

[4] Its translation to English is as follow: "When ready, please notify the experiment administrator to press SPACE key".

Figure 15: Calibration screen that is provided by TOBII T120 Software Development Kit (SDK). Yellow dots appear one by one and the participant is required to follow those dots. After all 5 dots appear, SDK returns a signal whether the calibration is successful or not. Therefore the software developer is able to proceed with the experiment or restart the calibration.

M-BART software and visual interface was developed in C# language and Microsoft Visual Studio 2013 platform (https://www.visualstudio.com) and integrated to TOBII T120 with the help of TOBII software development kit (http://developer.tobii.com).

Pupil sizes were initially not collected from three of the participants due to a technical problem. In some occasions, even after the eye-tracking calibration step TOBII T120 can posit problems when collecting pupil sizes. A real-time detector of this fault was implemented. The software indicated the administrator the ratio of the actual collected pupillary response without disturbing the participant. For this three participants, this situation was detected early in the experiment, experiments were immediately

Figure 16: Numpad that is designed and used in m-BART. The fundamental aspect of the keyboard is that it helps participant to control the keyboard without looking to it. The single button on the upper row pumps all balloons, and the buttons on the lower row collects rewards respectively.

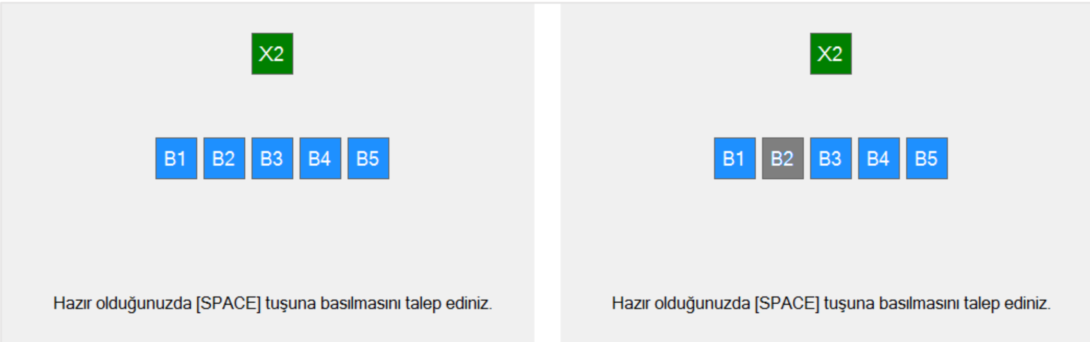


Figure 17: Screenshots from numpad warmup. Left: Numpad warmup screen. Right: Each keypress on the numpad changes button colors, providing a training for responding without looking down to the keys. The text is in participants' native language, Turkish. Administrator help is necessary, since the numpad does contain any key that is not required in the task. Participant cannot be requested to press the SPACE key from the regular keyboard neither, because that would break her eye contact with the screen. When this key is pressed, m-BART starts.

cancelled and participants restarted the task. Their previous (unfinished) runs were discarded and last runs were taken into consideration. Other than this, all other participants' data were intact. TOBII T120 is capable of collecting pupil dilation response in the presence of eye glasses. Normal vision was not required. All participants had normal or corrected to normal vision.

4.4.3. DOSPERT. DOSPERT survey decomposes natural risk taking behavior into 5 distinct domains: recreation, finance, health, social and ethic[5]. It comprises of 30 statements. Each statement belongs to one or two of these domains. Participants rate their likelihood of agreeing to that statement in a Likert scale of seven (Weber, Blais, & Betz, 2002; Blais & Weber, 2006). Questions of DOSPERT and their Turkish translations are given in Appendix A.

4.4.4. Data collection. As mentioned earlier, pupillary response has a refractory period of approximately 3-6 seconds. In order to correlate this physiological profile with the participants' collect/pump responses, we introduced a minimum of 3 s lock after each response. When a participant hit a particular button on the keyboard, outcome was displayed immediately, and buttons were disabled for an interval of 3 s to prevent an immediate secondary response. This lock was cued via a change of color on balloon reward labels. Their color changed to gray when responses were disabled and changed to black after 3 seconds, when responses were enabled. Because of the nature of pupillary response, the pixel size of the indicator and the change in the hue value was kept low in order to prevent a major change in the intensity of the interface. None of the participants reported a negative comment regarding this change.

[5] Test and retest reliabilities and verifications of these domains, and a general verification of the survey is provided in the original article (Weber, Blais, & Betz, 2002).

Participants were notified beforehand for this lock down. They were given unlimited amount of decision time over this interval, however pupil diameters only in the first three seconds were taken into consideration for data analyses.

Pupil responses are observed to follow a similar pattern after a decision. Pupil diameter shows a general initial increase, followed by a decrease to its baseline value toward the end of the (pupil) response. The nature of this task does not provide a separate inter-stimulus interval with a blank screen. Therefore unlike other experimental designs (Bradley, Miccoli, Escrig, & Lang, 2008) no initial pupil constriction was present for each trial. Because of eye blinks, the 3 s long trials occasionally contained missing data points. During data pre-processing, trials with missing (eye-blink) data that extends for more than 1/5 of the period were discarded. %86.1 percent of the raw data remained intact. Missing data in the remaining responses were approximated simply via a polynomial interpolation algorithm. After the interpolation, the percentage of the 3 s chunks that were available for analysis was %96.8 of the entire data set.

All data processing, including the aforementioned eye-blink data removal and missing data approximation, was also done with a software program, developed in C# language and in Microsoft Visual Studio 2013 platform.

4.5. Experiment 2: m-BART without Pupillary Response

A follow-up experiment with similar experimental setup was conducted to check for the effects of response times. The purpose of this experiment was to check whether the presence of 3 s locks to collect pupillary responses had a negative impact on the analysis of response times. We aimed to explore the idea that in the absence of 3 s locks participants could give responses in shorter times. Therefore a similar setup was developed without these locks to check whether the response times in the absence of these locks had a major effect on our assumptions.

4.5.1. Participants. 12 subjects (7M, 5F, age range = 23 to 32 years, mean = 25.1, stdev = 3.1) participated. All participants were university students or graduates from Middle East Technical University. Participants were administered the same DOSPERT survey. All participants gave written consent to participate.

4.5.2. Procedure. The procedure was similar to the previous experiment, except the data collection and data processing regarding the pupillary responses.

In order to collect participants' response times more effectively, 3 s locks were removed as well as their indicators. Instructions were also updated with respect to this change. Participants were free to press buttons immediately one after another. There were (similar to the Experiment 1), no upper time limit for their responses.

4.6. Simulation

In a simulation of m-BART, 5.000.000 agents completed the task. Agents were divided into 10 groups; namely 10, 20, 40, 80, 160, 320, 640, 1280, 2560, 5120. These numbers indicated the threshold at which the agents collected the balloon rewards. Main purpose of the simulation was to check whether there exist an agent that surpasses the scores of the participants (i.e. whether the agents achieved higher scores than the participants of Experiment 1 & 2). Therefore further agents were not developed. Results and a discussion of the simulation will be provided in the following chapters. The algorithm of an agent of the simulation is given in Algorithm 1.

Algorithm 1 m-BART agent

```
s: number of balloons in the global stack.
r: total reward.
g: limit of the agent.
c: number of balloons equal to or greater than g at each trial.

s ← 150
r ← 0
g ← [either one of 10, 20, 40, 80, 160, 320, 640, 1280, 2560, 5120 with respect to
agent's group]

while s > 0 do
        c ← number of balloons equal to or greater than g.
        if c > 0
                if c > 1
                        action: pump
                        s ← s – [count of popped balloons]
                else
                        action: collect
                        r ← r + [collected balloon value]
                        s ← s – 1
                end if
        else
                action: pump
                s ← s – [count of popped balloons]
        end if
end while

return r
```

4.7. Supplementary Experiment 1: Cups Task

4.7.1. Participants. 12 subjects (10M, 2F, age range = 22 to 51 years, mean = 32.8, stdev = 6.8) participated. Participants executed the task in front of their own PC's, in their own environment.

4.7.2. Procedure. Participants started the experiment with an interface that contained the instructions for the task, and they were also required to enter their names and their age. After supplying the required information they are allowed to start the task via a button press. The task is the exact copy of the Cups Task, with 100 consecutive decisions[6] (Figure 18).

This task is developed in C# programming language and Microsoft Visual Studio 2013 platform.

4.8. Supplementary Experiment 2: CGT

4.8.1. Participants. 11 subjects (9M, 2F, age range = 22 to 38 years, mean = 31.1, stdev = 4.3) participated. Participants executed the task in front of their own PC's, in their own environment.

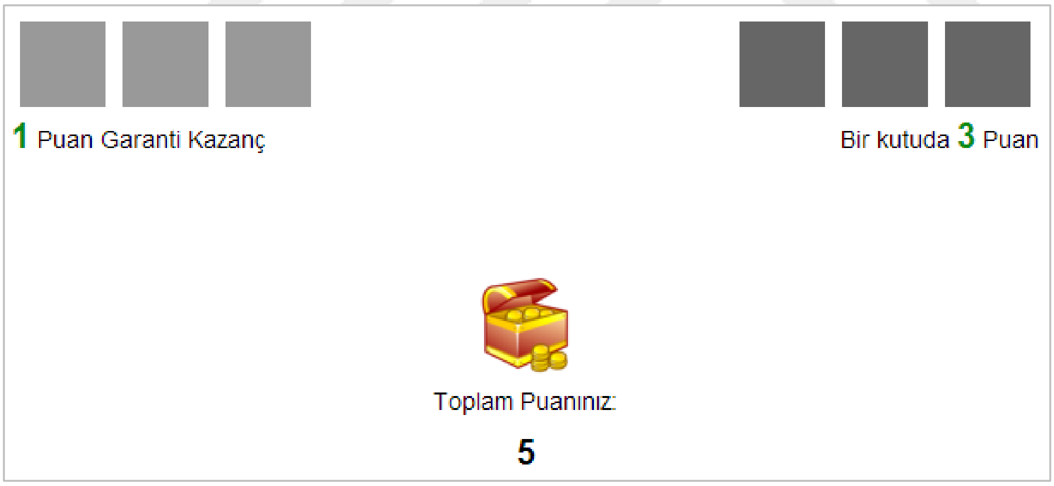


Figure 18: Screenshot from Cups Task. Participant receives a guaranteed 1 point reward (or punishment) if she decides on one of the left boxes. In one of the boxes on the right, there is a higher amount of reward/punishment, whereas the other boxes (on the right) are empty. Number of boxes and reward/punishment amounts change in each session (2, 3, and 5 boxes; 2, 3, 5, -2, -3, -5 rewards).

[6] English translation can be given as follows: On the top-left: "1 points guaranteed reward". On the top-right: "3 points reward under one of the boxes". On the center-bottom: "Your total score".

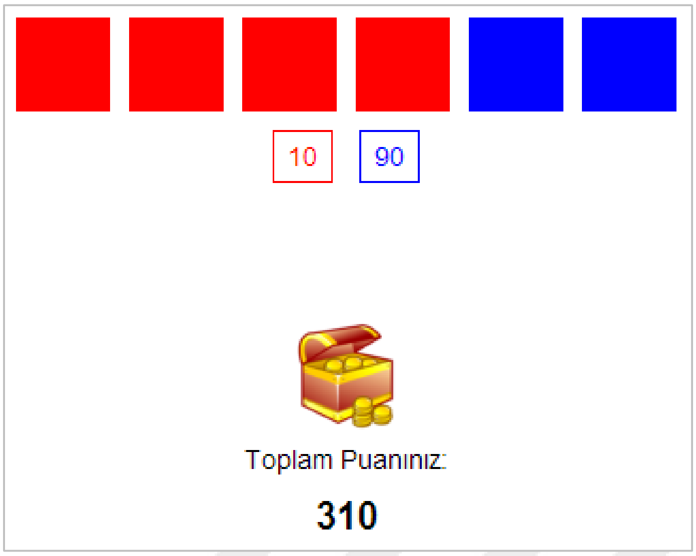


Figure 19: Screenshot from Cambridge Gambling Task. There is reward in one of the six boxes with equal probability. In each session, participant chooses red or blue. If participant's decision is correct, she gets the reward that is shown with that color. Number of red boxes and reward/punishment amounts change in each session (3, 4, and 5 red boxes; 10, 20, 30, 40, and 50 red rewards.

4.8.2. Procedure. Participants started the experiment with an instructions interface similar to the Cups Task. After supplying the required information they are allowed to start the task via a button press. The task is the exact copy of the Cambridge Gambling Task, with 100 consecutive decisions[7] (Figure 19).

This task is developed in C# programming language and Microsoft Visual Studio 2013 platform.

[7] English translation can be given as follows: On the center-bottom: "Your total score".

CHAPTER 5

RESULTS

Analyses on pupillary response were carried out on the maximum pupil diameter in the first 3 s following the participant response, namely *Maxpupil*. For each participant, *Maxpupil* values were normalized to [0, 1] range. Data analyses were done over these normalized values of *Maxpupil*, except for the figures that represent each individual's pupillary responses to give a more clear insight on the individual results. All analyses regarding pupillary response was done on the results of the Experiment 1.

5.1. Momentary Emotional States: Risk Taking States

The data analysis focused primarily on the hypotheses that were presented in the introduction. To recall:

Hypothesis 1. Participants are either in a more risk taking or a more risk aversive emotional state. These states can be modelled as dynamic system, and the predictions of this system can be observed via neurophysiological responses.

Hypothesis 2. Previous decisions and their outcomes can change the emotional states. These changes will be observed via tracking changes in neurophysiological responses.

Hypothesis 3. When presented with an identical trial more than once, participants will prefer the less risky alternative when they are in a risk aversive state and the more risky alternative when they are in a risk taking state.

Hypothesis 4. Natural risk taking attitudes has a general effect that distinguishes one individual from another. Participants with higher risk taking tendencies will appear in the risk taking state more.

We basically claimed that there must be emotional states that determine the decisions, and that these states can change with respect to outcomes of previous decisions. Therefore the objective of the data analysis was mainly to identify such states.

In a thorough analysis of all participants' experiment data, we found out that they were either in a state that they pushed their limits by risking balloons with higher values, or in another state that they responded more conservatively by collecting balloons that had relatively low values. We denote these two states as “risk taking states”. The former state is “risk taking”, and the latter is “risk aversive”.

Following **Hypothesis 1** and **Hypothesis 2** we claim that participants happen to be in either a risk taking state or a risk aversive state during the experiment. They change their states with respect to their actions and their immediate outcomes. In turn, their changing risk-taking tendencies have an effect on their collect and pump decisions to follow.

To realize these states, we attempted to define the heuristic (characteristic) function and state transition points on a simple mathematical basis. We implemented the heuristic function based on a single parameter called the “current maximum”. Then we labeled particular participant responses as the state transition points, namely the “turning points”. Definitions of *Current Maximum* and *Turning Point* are given in the following subsections. A table of abbreviations for the following definitions and equations are given in Table 4.

Table 4: Abbreviations that will be used to formulate the hypothetical model.

pd	*Pupil Diameter (normalized)*
cv	*Value of the most inflated balloon*
cb	*Value of the collected balloon*
dc	*Decision (pump / collect)*
st	*State (0: risk aversive / 1: risk taking)*
tp	*Turning Point*
cm	*Current Maximum*

5.1.1. Current Maximum. This is the reward value of the latest collected balloon. Its unit is in points. It states roughly the maximum amount that the participant risks at that particular point in the experiment. Following equation briefly states that if a balloon that is greater or equal the size of the current maximum is pumped, then the Current Maximum is increased (by a factor of 2; because the values are multiplied by two in m-BART). On the other hand, if the participant collects the most inflated balloon and if it is less than the *Current Maximum*, then the *Current Maximum* is decreased to the value of that balloon.

$$cm_i = \begin{cases} cv_{i-1} * 2, & (dc = pump) \wedge (cv_{i-1} \geq cm_{i-1}) \\ cv_{i-1}, & (dc = collect) \wedge (cv_{i-1} < cm_{i-1}) \wedge (cv_{i-1} = cb_{i-1}) \\ cm_{i-1}, & otherwise \end{cases} \quad (1)$$

$$(i = trial\ index)$$

5.1.2. Turning Point: This indicates the time when the participant changes her *Current Maximum*, either upwards or downwards. A pump response that increases a participant's *Current Maximum* indicates an *Upwards Turning Point* (tp = 1). A collect response at a reward value that is below her *Current Maximum* constitutes a *Downwards Turning Point* (tp = -1).

$$tp_i = \begin{cases} -1, & (cm_i < cm_{i-1}) \\ 0, & (cm_i = cm_{i-1}) \\ 1, & (cm_i > cm_{i-1}) \end{cases} \quad (2)$$

To clarify, consider a situation that a participant collects a balloon containing a reward of 160 (*Current Maximum* = 160). Afterwards she continued to pump and obtained a balloon with the same reward of 160 again. The following trial will be a turning point if she pumps -rather than collect- at that point (*Upwards Turning Point*). However, if she collects an 80 after collecting a 160, then this trial will be recorded as a *Downwards Turning Point* (Figure 20).

We assumed that these turning points were indicative of changes in the risk taking states of participants. Starting from an upward turning point, we assumed that the participant was in a risk taking state. On the other hand, starting from a downward turning point participant switches to a risk aversive state. Below, 0 indicates risk aversive, 1 indicates risk taking states.

$$st_i = \begin{cases} 1, & (st_{i-1} = 0 \wedge tp_i = 1) \vee (st_{i-1} = 1 \wedge tp_i \neq -1) \\ 0, & (st_{i-1} = 1 \wedge tp_i = -1) \vee (st_{i-1} = 0 \wedge tp_i \neq 1) \end{cases} \quad (3)$$

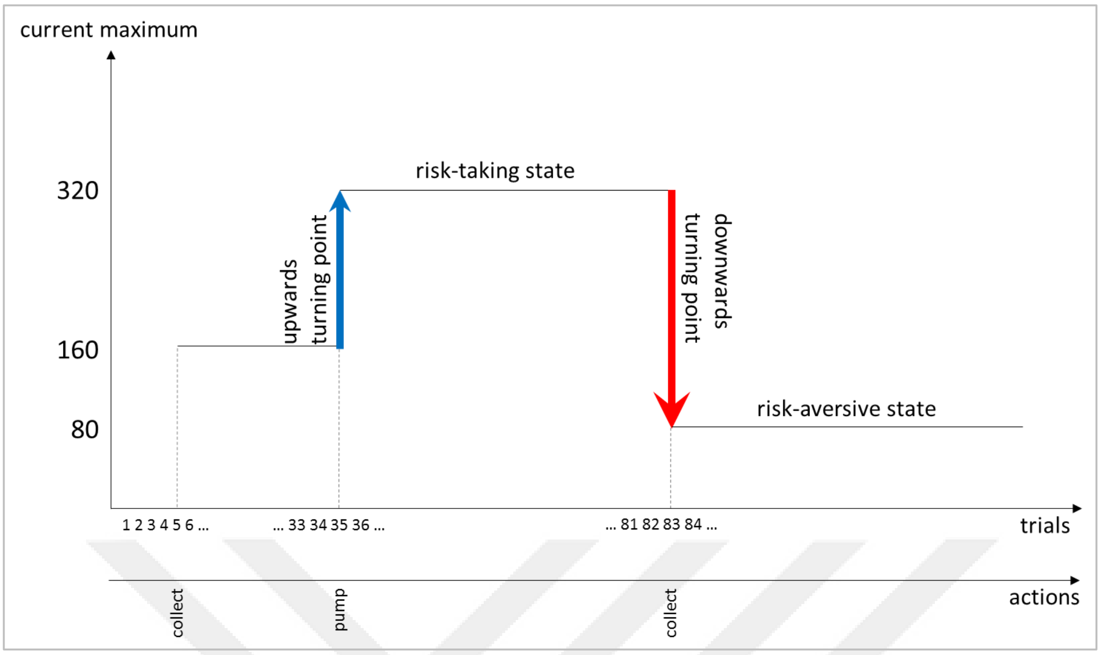


Figure 20: A demonstration of changes in the risk taking state. For clarity, assume we do not know the prior risk taking state until the first collect response at the 5th trial. At the 5th trial the participant collects a 160 reward. The current maximum is 160 then. In the 35th trial, she pumps a balloon with a reward of 160. This is an upwards turning point for the participant ($tp_{35} = 1$). Her current maximum becomes 320 and she enters the risk taking state ($[st_{35}, st_{83}] = 1$). At the 83th trial, she collects a balloon with a reward of 80. This represents a downwards turning point ($tp_{83} = -1$). From now on she is in the risk aversive state ($st_{83+} = -1$).

An algorithmic representation of state transition is as follows:

Algorithm 2 state transition

st: risk taking state
cm: current maximum

st ← "unknown"
cm ← "unknown"

while not at the end of participant responses **do**
  if the response is pump and the maximum value of the current balloons is equal to the cm
    cm ← [the maximum value of the current balloons]
    st ← "risk taking"
  else if the response is collect and the collected value is less than cm
    cm ← [collected value]
    st ← "risk aversive"
  end if
end while

The flow of the participants' states are visualized in Figure 21. For the 22 participants, a total of 402 state changes were calculated (M = 18.27, SD = 7.82).

5.2. Association Between Maxpupil and Risk Taking States

Regression test results revealed a significant relationship between each participants' risk taking states and *Maxpupil*. For all participants, pupil diameters are visibly larger in the risk taking state than in the risk aversive state (Figure 22, Figure 23 and Figure 24).

A dependent t-test indicates that the *Maxpupil* is significantly larger in risk taking state (M = 3.58, SE = 0.47) than in risk aversive state (M = 3.47, SE = 0.45), t(21) = -10.95, p < 0.01, r = 0.92. Table 5, Table 6 and Table 7 shows the details of the dependent test. Table 5 and Table 6 gives the statistics about two variables (risk taking and risk aversive states) and the correlations in between. Table 7 gives the detailed t-test results.

Table 5: Paired samples statistics for two states

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Risk Aversive	3.4693	22	.44888	.09570
	Risk Taking	3.5844	22	.47439	.10114

Figure 21: A visualization representation of state changes for 22 participants. Each line represents a participant. Lines represent the risk taking states throughout the experiment for each participant. Light colors represent risk aversive, dark colors represent risk taking intervals. The white intervals in the beginning of the experiment represent the initial trials that the state is not yet known.

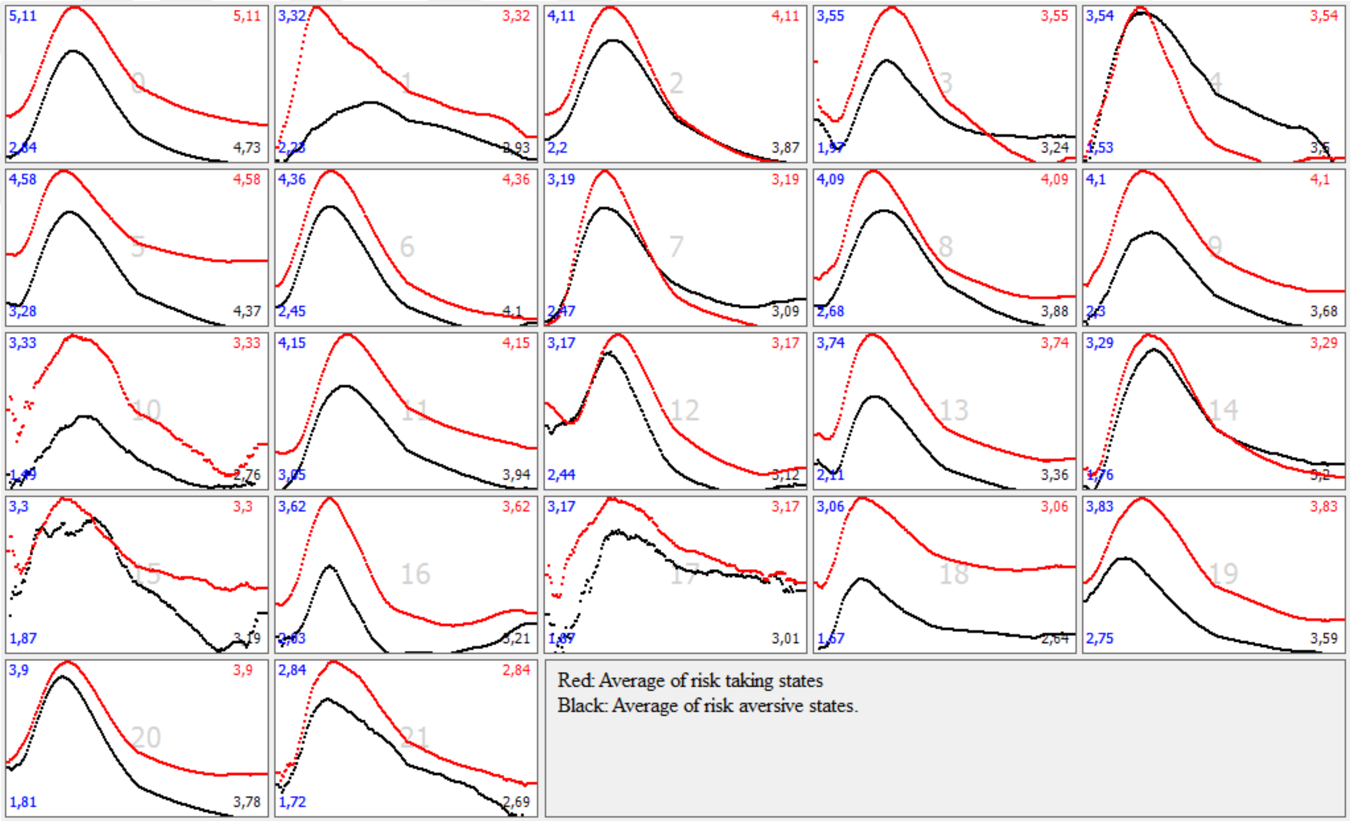


Figure 22: Averages of pupil dilation drawn separately for two risk-taking states. Each graph represents a participant (participant ID given in the middle). Red lines represent average of pupil diameters in risk taking state and black lines represent average of pupil diameters in risk aversive state. All graphs represent the first 3 seconds after decisions. Y-axis is generated by averaging pupil diameters point by point for the first 3 seconds. Blue values represent the highest and lowest pupil diameters for each participant. Red value is the highest pupil diameter for the risk taking, black value is the highest pupil diameter for the risk aversive states. Although useful, this figure gives only a rough visualization of these two response groups, since in each response, the actual moment of the response and the *Maxpupil* changes.

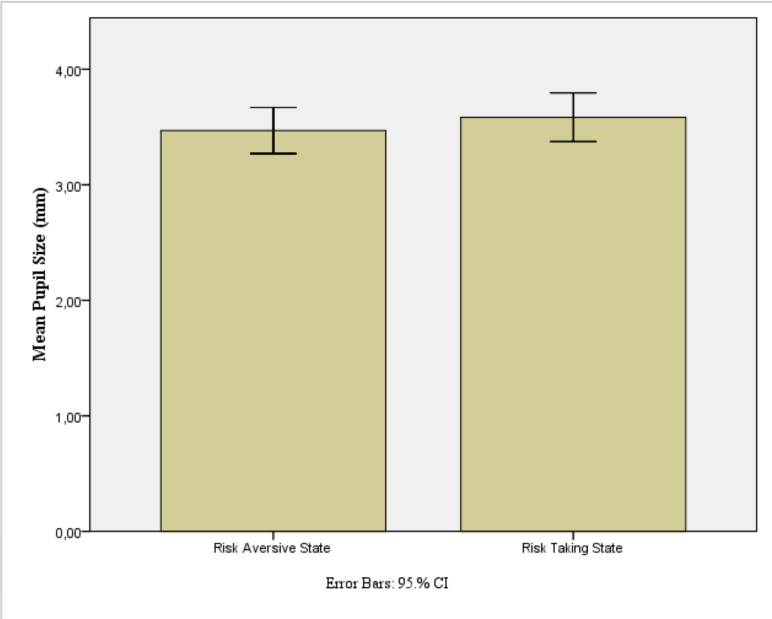


Figure 23: Pupil size averages with respect to risk taking states are given in a paired samples t-test. X-axis comprises of risk taking states. Y-axis represents pupil sizes of participants.

Table 6: Paired samples correlations for two states

		N	Correlation	Sig.
Pair 1	Risk Aversive & Risk Taking	22	.996	.000

Table 7: Paired samples test for two states. For each 22 participant, two average *Maxpupil* values for risk taking and risk aversive states were calculated. T-test results are given in this table. The results indicate that *Maxpupil* is significantly larger in risk taking state than in risk aversive state.

	Paired Differences					t	df	Sig. (2-tailed)
				95% Confidence Interval of the Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Risk Aversive - Risk Taking	-.12	.05	.01	-.14	-.09	-10.95	21	.000

In order to elaborate further on different participants' pupil dilation responses as a single measure, (the normalized *Maxpupil*) was tested against risk taking states. Similarly, a significant relationship between risk taking states and normalized *Maxpupil* was observed $F(1, 3352) = 782.911$, $p < 0.01$, $r = 0.43$ (Table 8).

With respect to these results, we concluded that the **Hypothesis 1** was verified.

Table 8: Regression Test Results for Pupil Sizes predicted by Risk Taking States. The *Maxpupil* of all participants were normalized to [0,1]. This table describes the regression test between risk taking states and the normalized *Maxpupil* values. It shows that the normalized *Maxpupil* is significantly predicted by the risk taking state.

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.286	.006		50.143	.000
	Risk Taking State	.098	.004	.435	27.981	.000

Dependent Variable: Normalized *Maxpupil*

5.3. Association Between Turning Points and Pupil Diameter Difference

Turning point is an arbitrary term that was priorly defined as a marker of changes between the risk taking states. Calculation of these markers depends completely on participant actions and their results; and not the pupil dilation data.

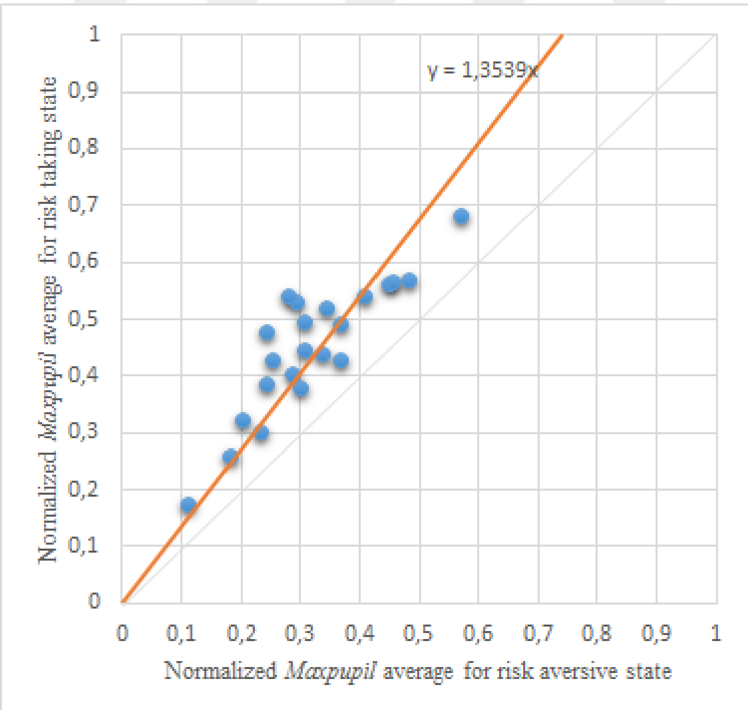


Figure 24: Scatterplot for risk taking and risk aversive states for 22 participants. Each dot represents a single participant. Y axis represents normalized *Maxpupil* average for risk taking state. X axis represents normalized *Maxpupil* average for risk aversive state.

Following **Hypothesis 2**, which stated that previous decisions and outcomes can change momentary emotional states, we further checked whether the difference in pupil sizes were descriptive of turning points. Differences in pupil sizes were calculated by subtracting current *Maxpupil* from previous action's *Maxpupil*.

A one-way repeated measures ANOVA showed that the pupillary responses were significantly different from each other; Wilks' Lambda = .277, F (2, 20) = 26.071, p = .000 (Table 9).

A follow-up dependent t-test indicated that *Maxpupil* differences in upwards turning points (M = .08, SE = .06) are significantly greater than when there is no turning point (M = 0.001, SE = 0.007), t(21) = 5.99, p < 0.01, r = 0.79. They are also significantly greater compared to downwards turning points (M = -0.12, SE = 0.08), t(21) = 7.4, p < 0.01, r = 0.85. Furthermore, *Maxpupil* differences in downwards turning points are significantly negatively greater than when there is no turning point (t(21) = -6.43, p < 0.01, r = 0.81) (Figure 25, Table 10, Table 11 and Table 12).

Table 9: One-way Repeated Measures ANOVA Results for Turning Points

Multivariate Tests[b]						
Effect		Value	F	Hypothesis df	Error df	Sig.
Turning Point	Pillai's Trace	.723	26.071[a]	2.000	20.000	.000
	Wilks' Lambda	.277	26.071[a]	2.000	20.000	.000
	Hotelling's Trace	2.607	26.071[a]	2.000	20.000	.000
	Roy's Largest Root	2.607	26.071[a]	2.000	20.000	.000
a. Exact statistic						
b. Design: Intercept Within Subjects Design: turning Point						

Table 10: Paired samples statistics for turning points. Upw. TP represents an *Upwards Turning Point* and Dwn. TP represents a *Downwards Turning Point*, for this and the following two tables.

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Upw. TP	.0814	22	.06298	.01343
	No TP	-.0014	22	.00699	.00149
Pair 2	Upw. TP	.0814	22	.06298	.01343
	Dwn. TP	-.1158	22	.08122	.01732
Pair 3	Dwn. TP	-.1158	22	.08122	.01732
	No TP	-.0014	22	.00699	.00149

Table 11: Paired samples correlations for turning points

		N	Correlation	Sig.
Pair 1	Upw. TP & No TP	22	-.224	.316
Pair 2	Upw. TP & Dwn. TP	22	-.497	.019
Pair 3	Dwn. TP & No TP	22	-.275	.216

Table 12: Paired samples test for turning points. For each 22 participant, three average *Maxpupil* difference values for were calculated. They were; the *Maxpupil* difference between an *Upwards Turning Point* and the previous decision. Second is the *Maxpupil* difference between a *Downwards Turning Point* and the previous decision. Finally the third is the *Maxpupil* difference between all other consecutive decisions. Three t-tests are given in the table. First test indicates that the *Maxpupil* difference is significantly larger in an *Upwards Turning Point* than when there is no turning point. Second test indicates that the *Maxpupil* difference is significantly larger in an *Upwards Turning Point* than in a *Downwards Turning Point*. Finally, the third test indicates that the *Maxpupil* difference is significantly negatively larger in a *Downwards Turning Point* than when there is no turning point.

	Paired Differences					t	df	Sig. (2-tailed)
				95% Confidence Interval of the Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1: Upw. TP - No TP	.08	.06	.014	.05	.11	5.986	21	.000
Pair 2: Upw. TP - Dwn. TP	.20	.13	.027	.14	.25	7.397	21	.000
Pair 3: Dwn. TP - No TP	-.11	.08	.018	-.15	-.08	-6.433	21	.000

This analysis further helps us predict the state change itself as given in the form of the following equation:

$$st_i = \begin{cases} 1, & (st_{i-1} = 0 \wedge a * (pd_i - pd_{i-1}) > b) \\ 0, & (st_{i-1} = 1 \wedge a * (pd_{i-1} - pd_i) > b) \\ st_{i-1}, & otherwise \end{cases} \quad (4)$$

Therefore the mathematical formulation of the problem of predicting state changes is provided with this equation. The two coefficients a and b in the equation were significantly calculated via an ANOVA (analysis of variance) test, $F(1, 64) = 120.920$, $p < 0.01$, $r = 0.80$. Results of this test is given in Table 13 and Table 14.

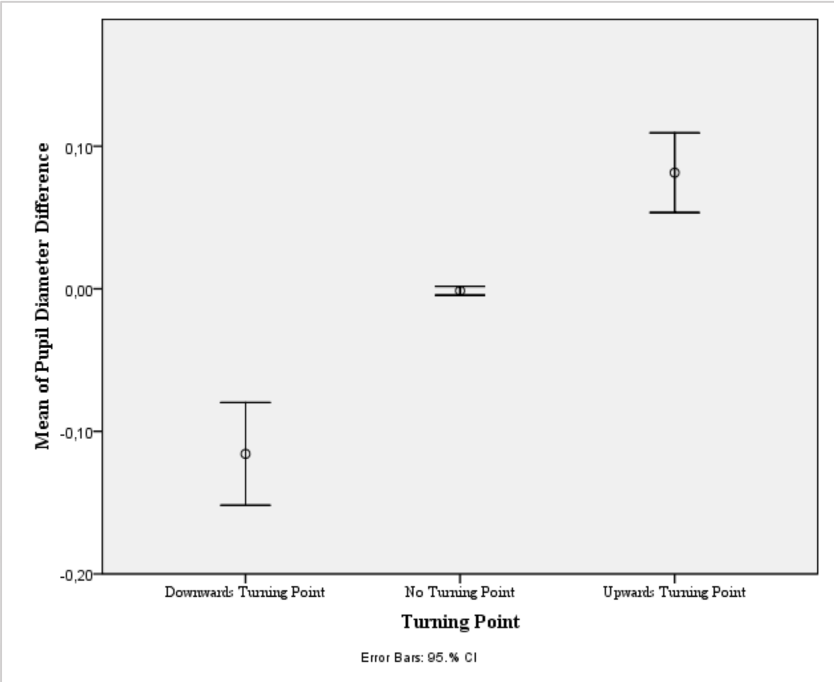


Figure 25: Differences in pupil sizes as predictors of turning points. In the x-axis, transitions from risk taking to risk aversive state are given on the left; transitions from risk aversive to risk taking state are given on right. The middle column represents no transition.

Table 13: ANOVA Test Results for Turning Points and Pupil Size Differences. As a complementary analysis to the dependent t-tests, an ANOVA was run. Dependent variable was the turning points and the independent variable was taken as the *Maxpupil* difference. Degrees of freedom represents the Maxpupil values for three turning point situations (upwards, downwards and no turning point) for each participant (22 * 3 - 1 = 65).

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28.772	1	28.772	120.920	.000
	Residual	15.228	64	.238		
	Total	44.000	65			

Predictors: (Constant), Maxpupil Difference
Dependent Variable: Turning Point

Table 14: Coefficients for Turning Points and Pupil Size Differences

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.079	.060		17.844	.000
	Maxpupil Difference	6.630	.603	.809	10.996	.000

Dependent Variable: Turning Point

With respect to the results that were described in this section, we concluded that the **Hypothesis 2** was also confirmed.

5.4. Association Between Maxpupil, Collect and Pump Responses

In addition to the risk taking states, we tested an alternative hypothesis in order to check whether it also fitted the experimental data and complemented our hypotheses. This alternative hypothesis briefly states that participant responses (either pump or collect) were correlated with pupillary response.

Experimental outcomes were put into a regression test. The dependent variable was again *Maxpupil*. An insight on the results can be obtained by inspecting Figure 26. This figure roughly demonstrates that *Maxpupil* values are not associated with the participants' responses. This result was also visible when normalized *Maxpupil* averages were plotted (Figure 27). Similarly, regression test revealed no significant correlation.

Therefore this alternative hypothesis was nullified in the light of these tests. This result was also in accordance to our initial hypotheses. We concluded that immediate responses (pump or collect) did not account for the participants' emotional states. If a participant is in a risk taking state her pupil diameter is observed larger, irrespective of her response. On the contrary, if she is in a risk aversive state, whether she presses pump or collect, her pupil dimeter becomes smaller.

5.5. Other Measurements

5.5.1. DOSPERT. Recall that the **Hypothesis 4** was regarding the natural risk tendencies and their holistic effects on experiment results. In order to elaborate on participants' risk taking attitudes and the relation between these attitudes and risk taking, DOSPERT survey was given to the participants. This survey is previously claimed to correlate with BART results (Blais & Weber, 2006). To test this hypothesis, in the Experiment 1, regression tests were run on DOSPERT domains (ethical, financial, health/safety, recreational, and social) and the length of the risk taking states (results of other tests regarding DOSPERT are also provided in the following sections).

DOSPERT survey results were averaged across five domains, and also a grand average is calculated. Furthermore, participants were categorized into four groups with respect to their DOSPERT results. 12 variables in total were checked against the length of the risk taking states (see Appendix B).

Additionally, no significant correlations in the Experiment 2 regarding DOSPERT survey was found. We were therefore unable to verify the **Hypothesis 4**.

5.5.2. # of total pumps and collects. A second test that was run regarding the DOSPERT results was between the aforementioned 12 variables, the number of total pumps and the number of total collects. We checked whether the participants with a higher level of risk taking attitude pumped balloons more. We did not find any significant correlation from these tests.

5.5.3. Total score. Total score (final amount of gain) was similarly tested against DOSPERT resulting again with no significant correlations.

5.5.4. Response times. Response times were found not to be significantly correlated with any of these aforementioned parameters and also with risk states in the Experiment 1. In the Experiment 2, without the 3 s locks, again no significant relation was found between response times and the risk taking states, $t(11) = 0.8$, ns, $r = 0.003$). Dependent t-test results are briefly given in Table 15.

5.5.5. Gender. Gender differences were found not to be significantly correlated with response times, risk taking states, # of total pumps, total scores and DOSPERT.

5.5.6. Eye blinks. Missing data that results from eye blinks were controlled against balloon pops (whether there is a pop or not), in order to determine possible effect of instantaneous audio-visual changes after balloon pops (i.e. the popping sound and the replacement of a big sized balloon with a small one on the screen). Missing data amount were found not to be correlated with balloon pops, $r(3418) = 0.012$, ns. (Table 16).

Table 15: Paired samples test results between Response Times and Risk Taking States in Experiment 2. The test revealed no significant differences between the risk taking states $t(11) = -0.8$, ns.

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Pair 1: Risk Aversive & Risk Taking	-61.24	263.00	75.92	-228.35	105.86	-.807	11	.437

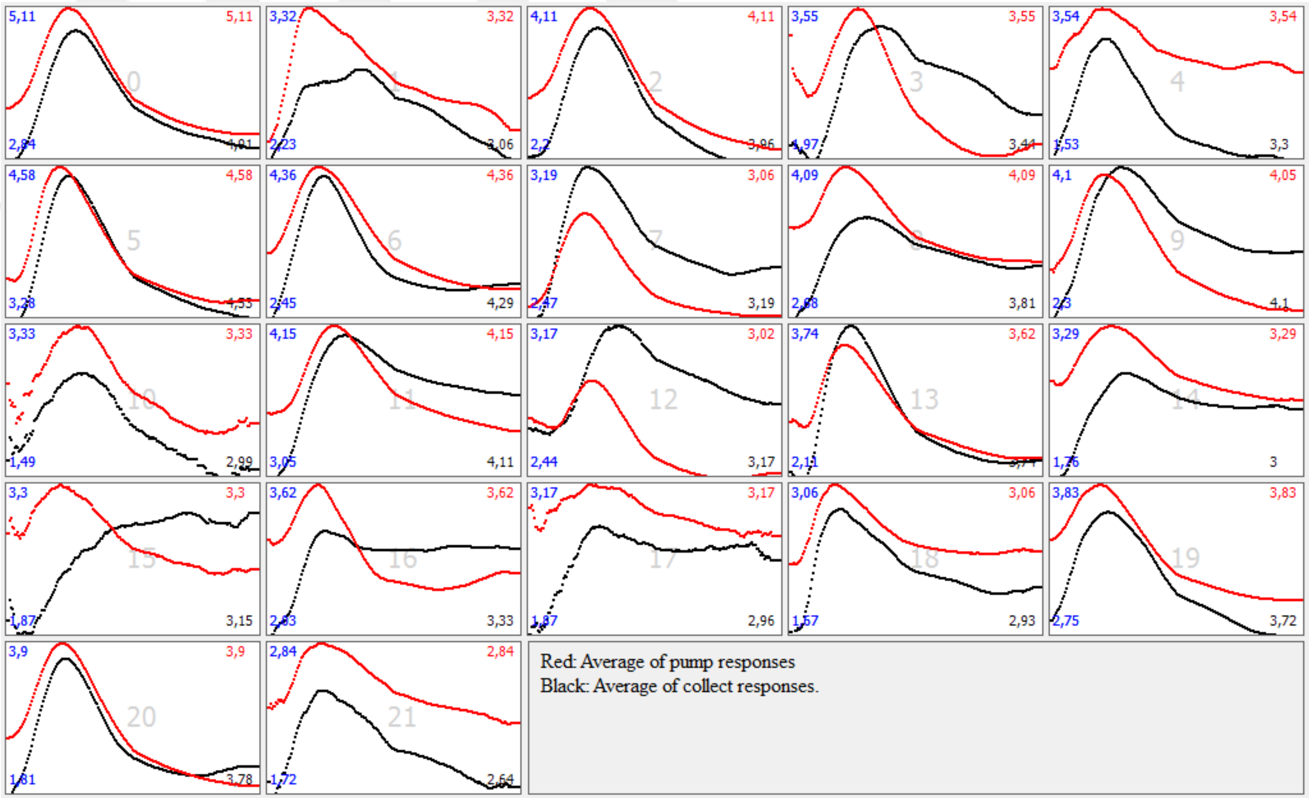


Figure 26: Averages of pupil dilation drawn separately for two response groups (pump / collect). Each graph represents a participant (participant ID given in the middle). Red lines represent average pupil diameters of pump responses, black lines represent average pupil diameters of collect responses. All graphs represent the first 3 seconds after decisions. Blue values represent the highest and lowest pupil diameters for each participant. Red value is the highest pupil diameter for the pump, black value is the highest pupil diameter for the collect responses. Although useful, this figure gives only a rough visualization of these two response groups, since in each response, the actual moment of the response and the *Maxpupil* changes.

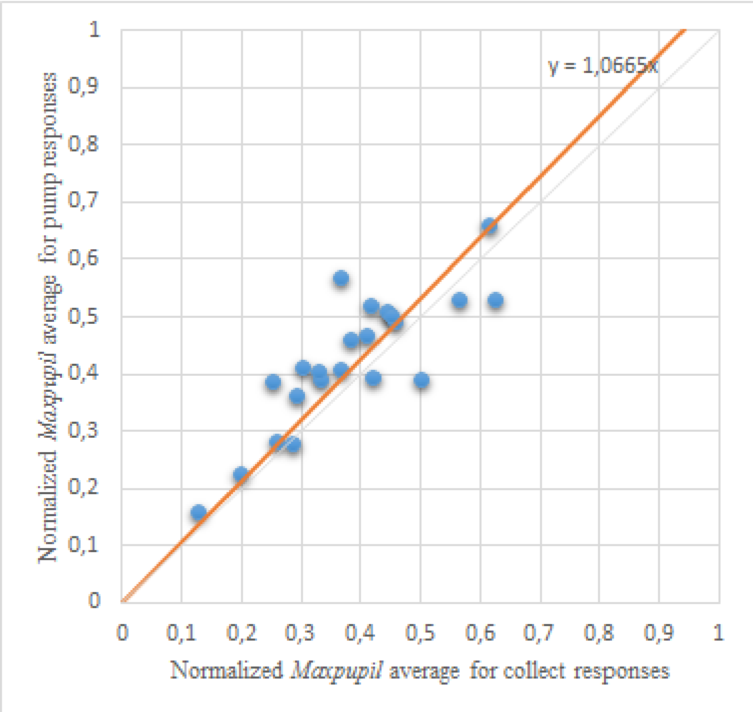


Figure 27: Scatterplot for collect and pump responses for 22 participants. Each dot represents a single participant. Y axis represents normalized Maxpupil average for pump responses. X axis represents normalized Maxpupil average for collect responses.

Table 16: Correlation between Missing Pupil Data and Balloon Pops. This results indicate that the percentage of missing pupil data does not correlate with the number of balloons that popped in the previous trial.

		Percentage of Missing Pupil Data	Balloon Popped
Percentage of Missing Pupil Data	Pearson Correlation*		.012
	Sig. (2-tailed)		.497
	N		3420
Balloon Popped	Pearson Correlation	.012	
	Sig. (2-tailed)	.497	
	N	3420	

* Correlation and significance values are irrelevant for the test between the same variable (shaded cells).

5.6. Validity of the Risk State Definitions and Dissociation of Risk States

We stated in **Hypothesis 3** that when presented with an identical trial more than once, participants would prefer different alternatives with respect to their emotional states. To test this hypothesis, such situations were analyzed with respect to the risk states that were described earlier in this chapter.

Balloon reward configurations were taken as the heuristic of indicating the identity of trials. For instance 40-40-80-80-160 reward values for the five balloons represented the identical situation with 80-40-80-160-40. We observed that some of these situations occurred more than once throughout tasks (regardless of the order of balloons). In some of them, participants made different decisions (same participant, making a different decision in the same situation). In other words, during the session, for the very same reward the participant pumped at one time but collected at the other time.

As a further investigation, we categorized these responses over the participants' risk taking states (Table 17). This investigation revealed a distinctive partitioning of the responses. Among the responses given to the same balloon configuration by a participant, the response is to collect iff (if-and-only-if) the participant is in the risk aversive state and to pump iff she is in the risk taking state. Given a total of 149 balloon configurations with exactly the same rewards, participants always collected in risk aversive state and always pumped in risk taking state.

Table 17: Risk States and Decisions. The total number of 149 in this table represents the situations that occurs to a participant more than once. For these situations, participants preferred to pump the balloons only if they were in the risk taking state. They preferred to collect only if they are in the risk aversive state.

	Collect	**Pump**
Risk Aversive	61	0
Risk Taking	0	88

To summarize, with respect to the presented results, we concluded that the **Hypothesis 3** is also confirmed. We will also be discussing these findings in the following chapter. We believe that this finding corroborates our hypothesis that participants' momentary emotional states determine their decisions.

5.7. Distribution of Collected Values and Pump Counts

In order to visualize the change in participants' pump-collect strategies, their actions were divided into 10 consecutive intervals, having equal length for each participant. For each interval, three values were computed: Pump counts, average of the collected

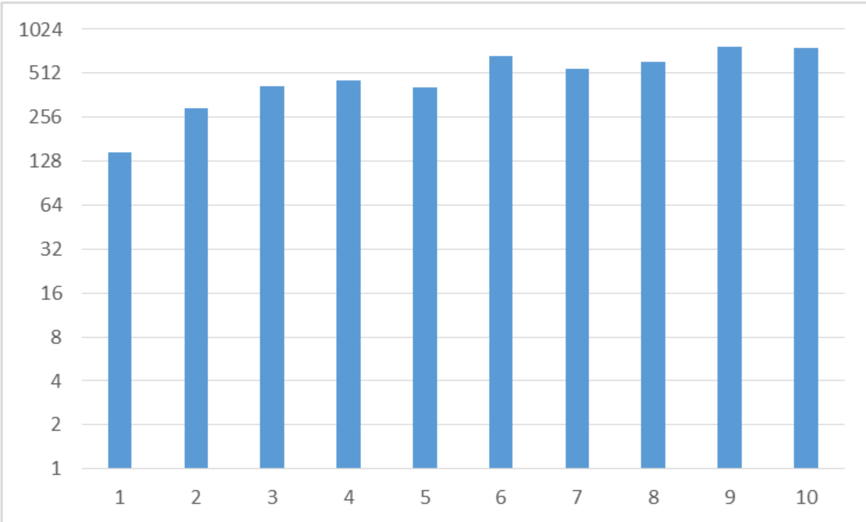


Figure 28: Average of collected values, grouped by intervals of equal length. These 10 intervals were generated by dividing each participant's actions into 10 consecutive groups. Each successful pump doubles the value in the balloon. Therefore average of collected values are visualized in a logarithmic scale. Constant in the regression equation dominates the coefficient of the interval variable (B0: 7.679, B1: 0.215)

values and pupil sizes. These values were then averaged over all participants (Figure 28, Figure 29 and Figure 30).

The first two figures imply a small change in behavior throughout the experiment. Both pump counts and average values of collected balloons tend to increase. However, constant values in regression equations dominate the coefficient of the variable in both

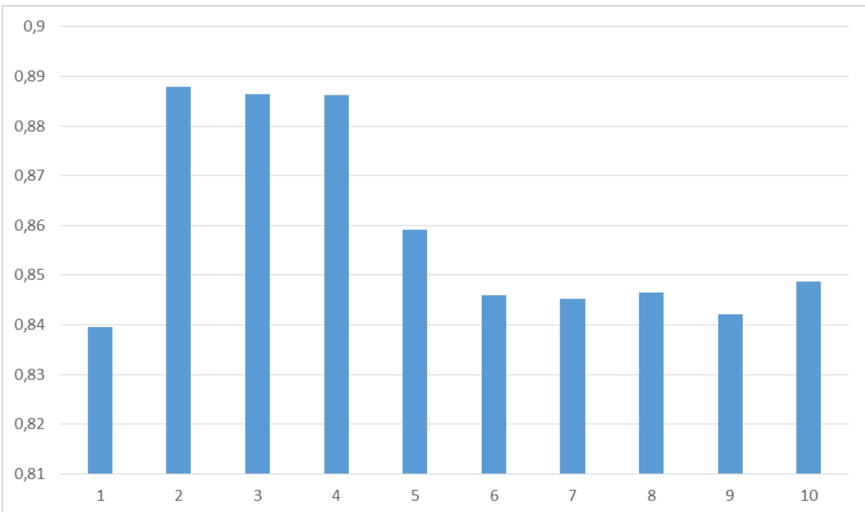


Figure 29: Average of pupil sizes, grouped by intervals of equal length. These 10 intervals were generated by dividing each participant's actions into 10 consecutive groups. Y-axis represents normalized *Maxpupil*.

analyses, suggesting a small effect (coefficients are given in captions). Finally, the last of these three figures suggests that there is no increasing / decreasing trend in pupil sizes. Its implications are also discussed in the following chapter.

Finally, Figure 30 represents how rewards were accumulated. The linear tendency of the reward accumulation implies that throughout the experiment, despite the nonlinear increase near the end, participants' were unable to find optimal ways of gaining more rewards.

5.8. A Comparison with the Normative Behavior

Results demonstrated in Figure 31 showed roughly that increasing the maximum balloon size did not increase or decrease the total reward.

Having run this simulation we concluded that a normative behavior in m-BART is at least not accessible by pumping indefinitely (or pumping less does not result in higher gains).

This proposed algorithm for these agents is arbitrary, and cannot be concluded as the best winning strategy for m-BART. However, participants' actual average reward in m-BART was 22289. This is distinctively below the agents' averages (146325). Therefore this allows us to conclude at minimum that there exists a pattern of decisions that can gain more reward than the participants. More discussion on this topic is given in the following chapter.

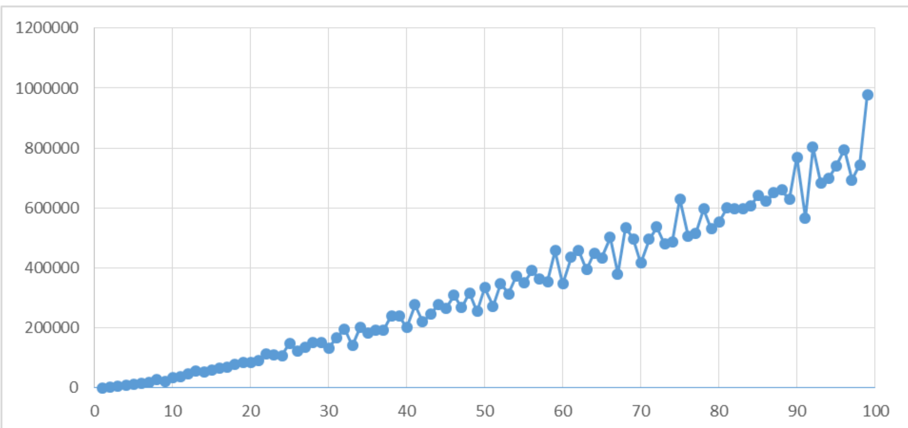


Figure 30: Accumulated rewards. X-axis represent consecutive actions, normalized between 1 and 100. Y-axis denotes the total gain of all participants. Participants' scores represent a constant increase in reward accumulation.

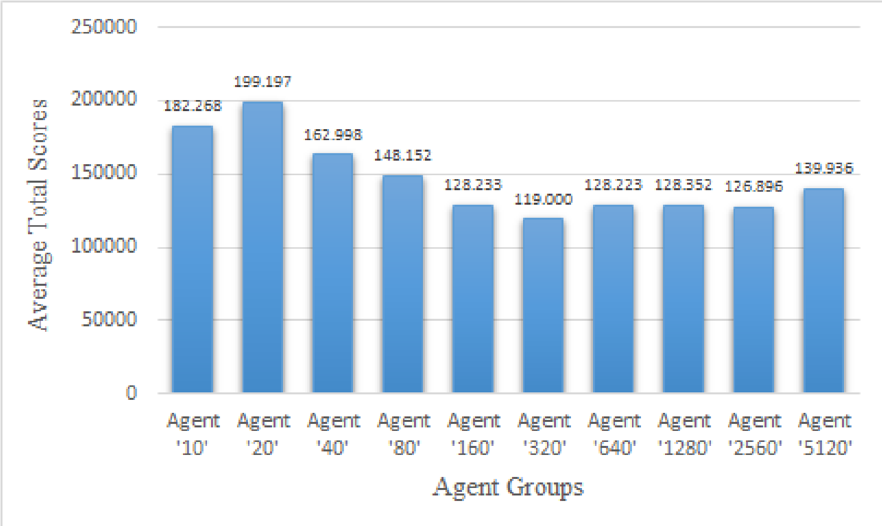


Figure 31: Normative behavior simulation. Y-axis denotes the average final score, gained by each group.

5.9. Cups Task and Hypothesis 3

To recall, we ran two supplementary experiments in order to elaborate on whether the same situation – different decision scenarios exist in a paradigm other than m-BART. The first of these experiments was a Cups Task.

As the first analysis, we checked whether there was a learning of the task heuristic by participants. To achieve a conclusion on this analysis, we specified the decisions that maximized the expected utility as the “correct decisions”. As aforementioned earlier, the task consisted of 100 trial. In each trial, participants were presented by two choices. Either of the two choices probabilistically results in an amount of reward. The amount of rewards and these probabilities (the expected values) are visible to the participant. We divided these 100 trials into 10 intervals with equal length. We found a high percentage of correct decisions starting from the first interval that did not change to the end (Table 18).

Table 18: Cups Task: Percentage of Correct Decisions. Starting from the very beginning of the experiment, participants did correct decisions with a high percentage that did not change more than %5 later.

Interval	1	2	3	4	5	6	7	8	9	10
Correct Decisions	78%	80%	82%	81%	73%	81%	75%	82%	74%	76%

In order to determine whether participants' decisions were similar throughout the task, we grouped each unique situation (e.g. box count: 2 and right reward: 3) and analyzed their decisions for these situations. Situations where the expected values were equal for alternative choices were discarded (e.g. box count: 5 and right reward: 1). We found that participants' decisions vary for similar situations even when there is a high percentage of correct decisions. Table 19 shows these results in detail. The percentages of the correct decisions represent the percentage of participants' decisions that had a higher expected value (EV). For instance, in the "box count: 2 and right reward: 3" case, 86% of the decisions were pressing the right button (EV(left) = 1, EV(right) = 1.5). This implies that at least for some of the situations participants were even deciding on the disadvantageous choice.

Table 19: Cups Task: Variance of Decisions on Similar Situations. The table indicates that participants' incorrect decisions exist in all situations. In two of the situations, incorrect decisions were made more than correct decisions (ones with less than %50).

Box Count	2	5	2	3	3	3	2	5	5	2	3	5
Reward	3	-2	-3	-2	2	5	-5	2	3	5	-5	-3
Correct Decision	86%	80%	60%	75%	22%	95%	69%	53%	43%	98%	54%	80%

We concluded that this result corroborated to the **Hypothesis 3**; the same situation – different decision scenario was also present in the Cups Task.

5.10. Cambridge Gambling Task and Hypothesis 3

Similar to the analysis in the Cups Task, we analyzed participants' decisions in 10 intervals. We found again a high percentage of correct decisions starting from the first interval that did not change to the end (Table 20).

Table 20: Cambridge Gambling Task: Percentage of Correct Decisions. Starting from the very beginning of the experiment, participants did correct decisions with a high percentage that did not change more than %4 later.

Interval	1	2	3	4	5	6	7	8	9	10
Correct Decisions	72%	74%	74%	75%	72%	74%	74%	75%	76%	69%

We ran a similar analysis regarding participants' decision variances. We grouped each unique situation (e.g. red box count: 4 and red reward: 30) and analyzed their decisions for these situations. Situations where the expected values (EV) were equal for alternatives were discarded. For instance, "red box count: 3, red reward 50" situation has equal EV's: EV(red) = 3/6 * 50 = 25. EV(blue) is also 25, because in this situation there are also 3 blue boxes with a reward of 50. We found again a variance in decisions for similar situations, similar to our results in the Cups Task (Table 21).

Table 21: Cambridge Gambling Task: Variance of Decisions on Similar Situations. The table indicates that participants' incorrect decisions exist in all situations. In one of the situations, incorrect decisions were made more than correct decisions (ones with less than %50).

Red Box Count	3	3	4	5	4	5	5	3	3	5	4	4	4	5	3
Red Reward	30	10	20	10	40	50	30	40	20	40	30	10	50	20	30
Correct Decisions	79 %	82 %	59 %	43 %	67 %	86 %	76 %	71 %	85 %	83 %	51 %	75 %	81 %	58 %	79 %

The results of this two supplementary experiments provided that the same situation – different decision scenario was also visible in two decision making tasks other than m-BART, therefore corroborating to the **Hypothesis 3**. Impacts of these results on our hypotheses are discussed in the following chapter.

5.11. Intensity Changes

As mentioned earlier, pupil constricts or dilates when a change in the illumination occurs; a phenomenon known as the pupillary light reflex. The graphical design (the user interface) was designed in order to prevent any major effects of intensity changes. Background color of the interface was specified as gray. The balloons were also in the same color; a small change to distinguish them from the background. The intensity change that was caused by the 3 s lock indicator was negligible.

In order to control for any possible effects of the change of illumination on our hypotheses and our tests, intensity changes for all possible scenarios that participants experienced were calculated by taking graphical screenshots and by averaging hue values of all pixels. Resultant intensity values were between 0.85 and 0.88 (M = 0.87, SD = 0.005). We checked for a correlation between intensity values and pupil sizes and found that these two variables are correlated, $r(3418) = 0.15$, $p < 0.01$ (Table 22). On the other hand, we found no negative impact on the correlation between pupil sizes and risk taking states, when this test was controlled against intensity values Table 23 shows briefly the correlation between pupil sizes and risk taking states; $r(3418) = 0.43$, $p < 0.01$. Table 24 shows the same correlation when intensity is controlled; $r(3415) = 0.41$, $p < 0.01$. We conclude from these results that the changes in the intensity values did not have a major impact on our findings.

Table 22: Correlation between *Maxpupil* and Intensity Values. The table indicates that there is a significant correlation between *Maxpupil* and intensity; $r(3418) = 0.15$, $p < 0.01$.

		Pupil Size	Intensity
Pupil Size	Pearson Correlation*		-.150**
	Sig. (2-tailed)		.000
	N		3420
Intensity	Pearson Correlation	-.150**	
	Sig. (2-tailed)	.000	
	N	3420	

* Correlation and significance values are irrelevant for the test between the same variable (shaded cells).
**. Correlation is significant at the 0.01 level (2-tailed).

Table 23: Correlation between *Maxpupil* and Risk Taking States. As shown in other prior tests, this table also indicates that there is a correlation between *Maxpupil* and risk taking states.

		Pupil Size	State
Pupil Size	Pearson Correlation*		.429**
	Sig. (2-tailed)		.000
	N		3420
State	Pearson Correlation	.429**	
	Sig. (2-tailed)	.000	
	N	3420	

* Correlation and significance values are irrelevant for the test between the same variable (shaded cells).
**. Correlation is significant at the 0.01 level (2-tailed).

Table 24: Correlation between *Maxpupil* and Risk Taking States - Intensity Controlled. When the intensity variable is controlled, the correlation between *Maxpupil* and risk taking states remains significant.

Control Variables			State	Pupil Size
Intensity	State*	Correlation		.413
		Sig. (2-tailed)	.	.000
		Df		3417
	Pupil Size	Correlation	.413	
		Sig. (2-tailed)	.000	.
		df	3417	

* Correlation and significance values are irrelevant for the test between the same variable (shaded cells).

CHAPTER 6

DISCUSSION AND CONCLUSION

Decision making is a complex process comprising of several aspects and components such as the learning of the task heuristics, strategy developing, emotions of participants, their effects, and natural risk taking attitudes. In this study, we primarily focused on capturing the temporal nature of a decision making task; how decisions effect each other, and how participants' emotions change during the task.

Our assumption was that, temporal aspects of a sequential decision making paradigm can be investigated through a task, which did not allow participants to learn its heuristics, which was emotionally engaging, continuous and externally valid. These properties were already highlighted previously in a review as preconditions for a decision making task to "bridge the gap" between neuroeconomics and naturalistic risk taking (Schonberg, Fox, & Poldrack, 2011).

When learning occurs in a decision making paradigm, participants tend to develop top-down decision strategies. They start grasping the task heuristics and they gradually make better-winning decisions. This is, for instance, the situation for decision making tasks without uncertainty (Orquin, Bagger, & Mueller Loose, 2013). We initially assumed that in such tasks it would be relatively difficult to capture the emotional aspect of decision making. To avoid learning, we chose BART in the first place, and then with the help of a preliminary experiment (described in the fourth chapter) adjusted popping probabilities and gain modifiers. In order to reduce the complexity of the task, we simplified particular aspects of BART that was not specifically related to our research questions, such as the three different colored balloons with different popping probabilities and the increasing popping probability with the inflation of the balloon.

In the particular context of testing our hypotheses, BART had a limitation. With only one balloon to be pumped, it was unable to capture different responses in the immediate response after a balloon pop. With respect to our hypotheses, we claimed that immediately after a balloon pop, there is a possibility that participants go through an emotional state change, and this change can be tracked through their next response. In the 1 balloon scenario, a balloon pop leaves participants with a deflated balloon where the only option is to pump again. As a side note; it can still be argued that in a one-balloon original BART setup, it would be possible to track long term effects and to capture the temporality of the task. Such an argument would claim that when a balloon pops, participants would pump less in the following session. However, our decision of 5 balloons was posited to track more immediate effects, which can be tracked from pupillary responses.

As a reminder; effects of learning and strategy developing is also subject to change during a decision making task. In different decision making tasks, during the course of the experiment, participants' decisions may change in terms of accuracy and duration. Although the word "dynamic" is sometimes used in these studies, they generally refer to the temporality of the situation; not a dynamic system comprising of states and transition functions. As mentioned earlier, this topic remained out of the scope of our study. However, we do not claim that dynamicity of emotional states do not occur in those studies. The purpose of our choice of BART and our modification was to eliminate any interference of such effects.

Requirement for the task of being emotionally engaging is primarily to reflect the effects of individual risk taking attitudes. It is also compulsory to trigger changes in the momentary emotional states of participants. For instance, in a decision making task where all win-loss outcomes are given to participants only after the completion of the experiment (instead of being given after each response), participants' decisions less likely effect their further decisions. "Cold case" of CCT (Columbia Card Task) serves as an example in this sense (see Chapter 3).

BART satisfies the learning and the engagement criteria. On the other hand it only partially satisfies the continuity criteria. We modified the task by introducing multiple balloons that are displayed together on the monitor, therefore providing a way to capture participants' immediate responses after balloon pops.

As a side note on the selection of BART, it must be noted that CCT can also be used in this context. It resembles BART and covers mostly all its functionality. In BART, participants pump the balloon a number of times and voluntarily decide to stop, if the balloon did not popped already. They earn the reward that was accumulated in the balloon. In CCT, participants open the cards one by one. The trial ends when the participant voluntarily stops or the card turns out as a "bad" card. If the participant voluntarily stops she earns the total reward that was accumulated from each opened card. It has further superior aspects, such that it allows parametrization of the reward amounts in cards, and also the win/lose probabilities (by initially displaying the number of bad cards in the desk). Our choice of BART was mainly related to the nature of pupillary response collection. In CCT, participants are required to fill numerical input values, therefore requiring an extensive use of a keyboard. This would be problematic when collecting pupillary response. In a pupil dilation task, where eye contact is crucial, we found BART to be more fitting. With the help of the aforementioned special keyboard, we achieved high eye contact in all participants.

Our claim was that the decisions in a sequential decision making task, at least partially, depended on the participants’ previous decisions and their outcomes; and this dependence could be observed through a physiological response. We chose pupil dilation as this physiological response, primarily because it was a known indicator for arousal (Partala & Surakka, 2003; Bradley, Miccoli, Escrig, & Lang, 2008) and risk taking (Preuschoff, Hart, & Einhäuser, 2011; Jepma & Nieuwenhuis, 2011; Fiedler & Glöckner, 2012).

In accordance to our hypotheses, we found that the decision making behavior in a sequential decision making task could not solely be analyzed via individual participant responses. With respect to the **Hypothesis 1**; when we categorized the participants' responses into two states, namely risk taking and risk aversive, it allowed us to better predict the physiological response (pupillary response). Furthermore, in a follow-up analysis, we tested pump/collect responses against pupillary response and were unable to find a correlation between them. This also allowed to conclude that when decisions were investigated independently, it was more difficult to account for participants’ emotional states. Pupillary response does not vary depending on the momentary decision. It varies with respect to the emotional state the participant is currently in.

In accordance to the **Hypothesis 2**, we furthermore predicted participants’ decisions on critical points (turning points) via the differences in pupil dilation. Our analysis showed us that if the pupil dilated/constricted in a decision particularly more/less than the previous one, it could be an indicator of the current decision.

Our observations further showed that in a sequential decision making task, when participants were not allowed to develop strategies and were emotionally engaged, they could respond to similar stimuli differently throughout the task. This observation were in agreement with **Hypothesis 3**, stating that there must have been momentary emotional states that were responsible for these differences. When we grouped such responses (with the help of computed parameters *Turning Point* and *Risk Taking State*), we found that the response differences were in line with the momentary emotional states (*Risk Taking States*) the participants were in. Their changing perception of risk had a certain effect on their behavior, which can be tracked via pupillary response.

6.6. Towards a Model

To summarize again, in a follow-up analysis of the data, we did not find a relation between pump/collect responses and pupil dilation responses. We argued that the physiological response was the result of a more general psychological state (risk taking or risk aversion); and not a product of a singular action of risk taking (i.e., pump). We defined state changes (turning points) with respect to participants’ actions (Equation 1, Equation 2 and Equation 3). We argued further that state changes could be tracked (predicted) via pupillary response (Equation 4). In a further analysis, we found that the turning points were actually in correlation with pupil size differences. We successfully found coefficients for our equation of state transitions, by running a GLM analysis.

With respect to these results and statistical analyses, we believe that the emotional aspect of decision making can be formulated into a model. Our proposed model states that each outcome of participant action (decision) triggers a change in her somatic state (as observed from pupillary responses in our case). This is basically in correlation with her expectations and the degree of how much they are satisfied. Nature of this change determines the change in her risk taking state; whether her risk taking state changes or not. Finally her risk taking state determines her next action (Figure 32). State transitions of such a model can also be visualized as in Figure 33. If a participant is in a risk taking state, and she approaches a downwards turning point, she will switch to a risk aversive state. If she is in a risk aversive state, and she approaches an upwards turning point, she will switch to a risk taking state.

Our hypotheses also involved an effect of participants' natural risk taking attitudes. We were unable to find any effects of these attitudes to this model. Although the test between DOSPERT results and the risk taking state lengths were marginally significant, we rejected this hypothesis (**Hypothesis 4**). However, the model can be improved with future studies on this topic. Natural risk taking attitudes of participants is already accepted as a factor in similar models (Lerner, Li, Valdesolo, & Kassam, 2015). Affective nature of decision making, and the dynamic nature of the effects of emotion is becoming a trending topic of research (Taskin & Gokcay, 2015; Phelps, Lempert, & Sokol-Hessner, 2014). Phelps et. al. (2014) gave a similar model as their conclusion in their review (Figure 34). It is a similar interpretation of results; also

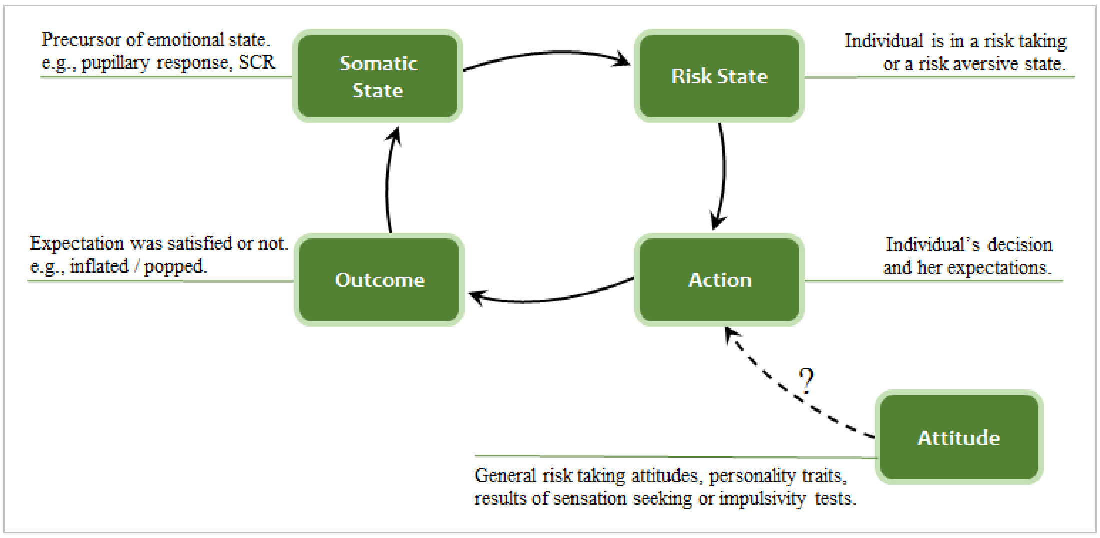


Figure 32: A hypothetical model with respect to the experimental results. Previous outcome triggers a change in the somatic state. Nature of this change determines the risk taking state of the participant. Finally, current state determines the next decision and action. Effects of risk taking attitudes and personality traits could not be realized in this study.

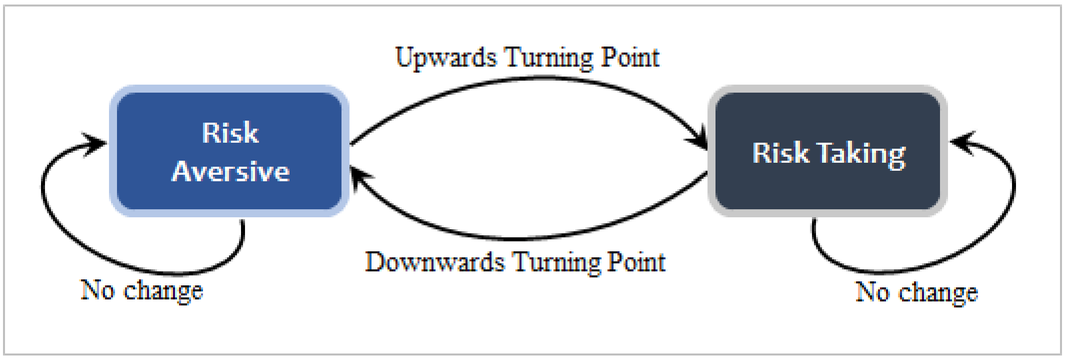


Figure 33: State transitions that occur in in the experiment. Participant changes her state on turning points. She stays in her state otherwise. State changes (or the absence of state changes) can be predicted via differences in pupil dilation.

including effects of incidental influences such as mood or weather. Therefore we preferred not to remove the box that represented these effectors in the model, and kept it as connected via a dotted line. We believe that future studies would help reveal the contributions of other effectors that we could not account for; such as risk taking attitudes, personal traits and mood.

6.7. Methodological Considerations on BART

It is possible to evaluate particular aspects of m-BART with respect to the review in the previously mentioned web site (http://www.impulsivity.org/measurement/BART). As mentioned earlier, we specified the total number of balloons to 150, which was considerably greater than the original task (90). It was observed that in BART, risk taking tendency increased after only around 30 balloons (Wallsten, Pleskac, & Lejuez, 2005). That was also the case in our observations (Figure 30). We observed a small change in pump-collect strategy in participants. Although the participants pumped more and they collected higher values in the course of the experiment, both of these tendencies were only marginal (Figure 28 and Figure 30). As verified from the results, they did not have a negative impact on the pupillary response analysis (Figure 29). One possible explanation might be that since there was no monetary reward, participants preferred risking more towards the very end of the experiment as an exploration of possibilities. As a future work, running m-BART with a larger number of balloons or introducing a monetary reward would help answer this question better.

We also observed that there was a nearly linear accumulation of rewards, implying that this number of balloons did not lead participants to a better-winning strategy (Figure 30). It also corroborated to our assumption that our design of m-BART prohibited learning. We believe that the increase that is observed at the very end of the experiment was mainly due to a different kind of understanding. Noticing that there remained a very few balloons, participants might have explored the idea of pumping “to the end”; therefore resulting in unusual gains for some of them. Again, absence of an actual monetary gain would have nurtured this behavior. A repetition of the same experiment with a monetary reward would help clarify this assumption.

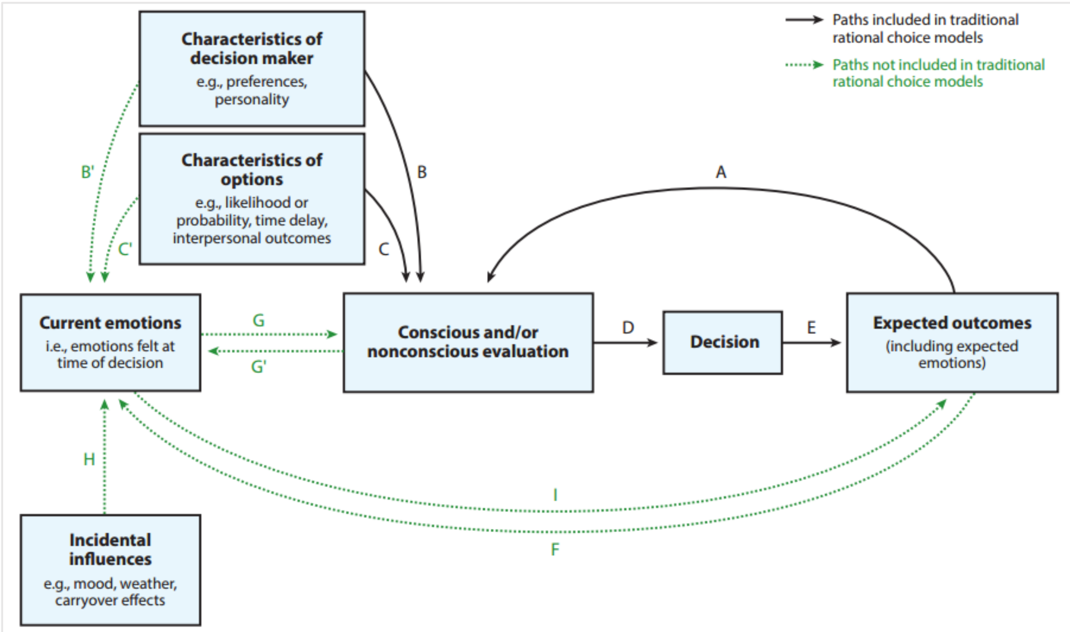


Figure 34: A proposed model of emotional influences on decision making (Lerner, Li, Valdesolo, & Kassam, 2015, p. 815). It is a similar interpretation of results; also including effects of incidental influences such as mood or weather.

Another methodological consideration is regarding on the design of scoring and reward/punishment amounts and probabilities. In our representation, after the preliminary experiment, we followed a partially different approach than the original task, which makes them incomparable. However, after our analysis on the results and our simulation, we can safely assume that our approach did not lead participants to develop an ultimate-winning strategy. It must also be noted that the strategy that is used by the simulated agents was developed via a limited set of trials. Via an alternative method such as an artificial intelligence algorithm, a better winning strategy can be found. Even though the participants were not able to develop their better-winning strategies, a future work on this would further contribute to our discussion and our conclusions.

The difference between the average total scores of participants and agents is also worth to note. The most important result of the simulation was that it proved that there existed an algorithm that gained more reward than the participants. But the difference is still worth to discuss. The only shortcoming we thought of is on comparing means of two unequally sized groups, which can be problematic while interpreting the results of the simulation (22 participants against 5 million agents). M-BART provides a very large branching. It is highly possible that even if the very same participants had run the m-BART one more time, their scores would have been visibly different.

One last remark on BART's methodological considerations is its test-retest reliability. BART has been noted to have a 0.77 test-retest correlation. Participants' scores from consecutive BART trials were in correlation with their former results with a resemblance rate of (r = 0.77, p < .001) (White, Lejuez, & de Wit, 2008). We leave this kind of a test as a future study. Because of its similar characteristics, we believe that a similar correlation would also been found in m-BART. However, such a test remains a future work.

6.8. Limitations of the Thesis

With this thesis, we aimed to explore the fundamentals of changes of emotional states in a decision making task. To the best of our knowledge, this is the first study that investigates this aspect of decision making tasks. Therefore, several investigation opportunities were left unexplored. These aspects will be given as the limitations now.

The first limitation of the study regards the choice of pupil dilation response as the only bodily response. Therefore the proposed model happened to be verified by only this measure. In order to elaborate more on our hypotheses, collecting more bodily (such as SCR) and neural responses (such as fMRI, fNIRS or EEG) would be helpful. It is possible that the characteristics and limitations of these techniques would require a different task and a different task design. However, each technique could help explore the bodily or neural underpinnings of the changing behavior in its own context.

Nature of pupillary response also forced us to inject 3 s of locks between responses. As mentioned earlier, after each response, buttons were disabled for an interval of 3 s to prevent an immediate secondary response. In Experiment 2, we aimed to elaborate on a situation where no such locks existed and participants could freely respond when they decided. We observed that in such a situation, average response time was less than 0.5 s. Yet, with respect to the analysis provided in the results, we did not observe an effect of response times over risk taking states, and we concluded that response times did not have an impact on the hypotheses. However, the considerably big difference between 0.5 and 3 seconds may also encourage follow-up studies with different neurophysiological responses other than pupil dilation.

Another limitation can be on the number of states. Regarding the formulation of the model, a two-state system was simply assumed. Although the experimental results and the data analysis supported this assumption, alternative hypotheses (e.g. three or more states) were not investigated and a comparison among them were not done. Also as a future work, more sophisticated (as in the preliminary experiment, for instance) or different experimental setups can be introduced that allow investigation of these alternative hypotheses.

Last but not least, selection of DOSPERT survey must be counted as a limitation. In both Experiment 1 and Experiment 2, we did not find any significant correlations among DOSPERT results and other experimental variables. Therefore we could not find the chance to debate on and to analyze individual differences and their effects on decision making. Furthermore, reliability and validity tests were not done to the Turkish translation, which can be taken as a future work and a possible improvement.

There is also the possibility that the sample space was insufficient to find a correlation with DOSPERT results. A sample space of 22 participants was considerably smaller than the original study; which consisted of 359 participants (Blais & Weber, 2006). It must be noted that the test between DOSPERT results and risk taking state lengths were marginally significant; $F(21) = 3.327$, $r = .378$, $p = 0.083$ (Table 25). A repetition of this test with more participants might provide a significant result.

Choosing a similar risk attitude scale such as Business Risk Propensity Scale (Sitkin & Weingart, 1995) or Risk Taking Index (Nicholson, Soane, Fenton-O'Creevy, & Willman, 2005) would contribute to this discussion. Observing or not observing an effect of these scales would help us elaborate more on the natural risk attitudes. Collecting different types of information with a working memory test battery or with personal trait surveys such as Sensation Seeking Scale (Zuckerman, 1994), Impulsivity Scale (Eysenck, Pearson, G, & Allsopp, 1985) or Retrospective Behavioral Self-control Scale (Marcus, 2003) would also provide different measures of analysis. Investigating the effects of long term emotional states (mood) would also be a valuable contribution to our model (de Vries, Holland, & Witteman, 2008; Buelow & Suhr, 2013; Lauriola, Panno, Levin, & Lejuez, 2014). Observing effects of these attributes would help us refine our proposed model.

6.9. Future Work and Implications

We strongly believe that further studies are necessary to elaborate more on our hypotheses.

These further studies may include other neural and bodily responses in addition to pupil dilation. As mentioned earlier, our choice of BART over CCT (comparatively more parametric and functional) was due to the nature of a pupil dilation task. In further studies CCT may be preferred with respect to the nature of the task.

A corollary regarding CCT can be on the cold version of this task. CCT provides hot and cold options. Hot version is the regular task, where participants open cards or stop after each outcome. This version resembles BART in this sense. In the cold version, participants decide on the number of cards to be opened in the beginning of each session and watch the cards to be opened according to their initial decisions. No distinctive skin conductance response (SCR) was observed in this (cold) version of CCT. A future work would be to run CCT with these two versions and check for participants' responses to similar situations. Following the **Hypothesis 3**, more varying decisions (same situation – different decision) would occur in the hot version than in the cold version.

As a last word on the choice of BART, we did not construct further experiments that included pupillary response (or any other type of physiological or neural responses) to test our hypotheses on any other type of task other than it. We ran a Cups Task and a CGT experiment as a means of testing varying decisions, without the pupillary response. Modifying other tasks (CCT or any aforementioned ones), or inventing novel tasks that are suitable for collecting pupillary response would be interesting corroborations to our hypotheses and a means to validate them with further data sets.

From the results of the two supplementary experiments, we identified a ceiling effect (regardless of experimental parameters, participants did correct decisions most of the time) in both of them (suggesting no learning). At the same time, we observed again that participants gave different decisions on similar situations. In some cases participants even made the non-optimal decision more than the optimal (higher expected value) decision. A thorough analysis of these results is incomplete and it remains as a future work. However, we believe that this preliminary results on the inconsistency of decisions is in accordance to our hypotheses, in the sense that participants do different decisions on similar situations on experimental paradigms other than m-BART even when there is a ceiling effect.

One corollary may be on a particular argument against SMH and IGT. This argument (the Prominent-B argument) focuses on the evidence that when ranked individually, deck B (one of the disadvantageous decks) remains the most attempted deck in IGT. Classical IGT task compares attempt amounts between advantageous and disadvantageous decks in total. When analyzed individually, attempts on B is greater than both C and D. Lin et. al., (Lin, Chiu, Lee, & Hsieh, 2007) designed a novel alteration of IGT, in which (healthy) individuals are given either AACC or BBDD configurations (or their counterbalanced versions). The intriguing part is that win-loss frequencies of these pairs are the same (between A and C, and between B and D). AACC configuration replicates Bechara's findings. On the other hand, participants displayed no tendency to neither of decks B and D. In a follow-up study, Chiu, et. al. (Chiu, et al., 2008) equalized gain-loss frequencies of four decks, and found that decks A and B are actually preferred rather than decks C and D. Evaluation of these findings led to the hypothesis that the tendency to B (and to both A and B in the second experiment) is related to its lesser frequency of losses, and that this implicates the role of VMPFC as an impulse inhibitor. To summarize, they briefly suggested that in a decision making task under uncertainty, when an alternative wins repeatedly it becomes more and more favorable by the participant. And later, even it loses it becomes participant's persistent choice.

In the light of our findings, we believe that it is possible to explain the Prominent-B phenomenon in IGT with respect to the task's dynamic nature. When more winning cards appear in a row, the probability of participants to switch to the risk taking state increases. And once in the risk taking state, participant continues to take risk until she reaches a threshold to switch back again. A future work may comprise of analyzing IGT and the counter argument as a dynamical system, by defining the heuristic value and state transition function, similar to this study.

Another corollary may be regarding the human computer interaction (HCI) studies and applications. Real-time detection of momentary emotional states is a trending topic in HCI studies (Peter & Beale, 2008), computer-based learning (Shen, Wang, & Shen, 2009) and even computer games (Jones & Sutherland, 2008; Sykes, 2010). In this study, we showed that pupillary response is an indicator of these states. As of today, technology of collecting pupillary response requires strict laboratory and lighting conditions, making it less suitable for HCI applications that are most likely to be run on real-life environments. Nevertheless we can state that possible future developments in this technology would contribute HCI studies by providing them an additional method to retrieve affective information.

Intensity changes (different intensity values for different situations) occurred throughout the experiment. This was a result of different balloon sizes, remaining number of balloons and changing numeric values on the screen. We found a small effect of intensity changes on pupil sizes. This was a well-known phenomenon, called pupillary light reflex. When we controlled this variable in our tests, we found out that our tests were mainly intact.

We believe that every decision making study that collects pupil sizes and consist of different visual interfaces for different decisions requires a check on changing intensities. Even in the case of m-BART, where only gray balloons change sizes on a gray background, there happens to be changes on intensities. Even though these changes were very small (in a range between 0.85 and 0.88), we found an effect on pupil sizes. We believe that in every future study that has similar characteristics, should include this control; which happens not to be a common practice as of today.

One potential area of future work would be to investigate differences of the changes in risk taking patterns in different age groups. Decision making and risk taking behavior and their neural underpinnings undergo changes in adolescents (Lejuez, Aklin, Zvolensky, & Pedulla, 2003; Hooper, Luciana, & Conklin, 2004; Eshel, Nelson, Blair, Pine, & Ernst, 2007; Figner & Weber, 2011; Blakemore & Robbins, 2012; Smith, Xiao, & Bechara, 2012). Adolescents, in general, display a more risky behavior and less recruitment of prefrontal cortices than adults. An analysis of temporal characteristics of their decisions would reveal further aspects of this dissociation.

We checked for possible effects of gender on risk taking state lengths, total scores, # of pumps, response times (in Experiment 2) and DOSPERT results. We were unable to find any effect in these tests. We concluded that gender did not have a major effect on our hypotheses.

Finally, data analysis can also be counted as a future work. The dynamicity that is offered in the thesis can also be analyzed as a drift-diffusion model (Ratcliff, 1978; Ratcliff & McKoon, 2008). With such an analysis, it would be possible for instance to see whether an accumulation of balloon pops caused turning points or not. Additionally, alternative models can be developed to account for the data, such as a hidden Markov model – HMM (Rabiner & Juang, 1986). A successful HMM would provide a probabilistic representation of risk taking states that the decisions depended on. In short, both analyses could provide alternative representations of our model.

Regarding the data analysis, statistical tests can be improved by taking states and actions as categories and running categorical data analyses.

6.10. Conclusion

Chronologically, theories of decision making that were developed in the early days of behavioral economics concentrated primarily on modeling universal decision making strategies, regardless of individual differences. In time, these theories were challenged as being insufficient to explain human behavior. With the help of developing neuroimaging techniques, analyses on neural and bodily responses allowed individual differences and personal risk taking attitudes to enter the picture of neuroeconomics. We now know that individuals give different behavioral / neural / physiological responses to similar choices with respect to their natural risk taking attitudes, their scores on impulsiveness scales, and in accordance to several other external measures related to decision making as well.

In the scope of this thesis study, we attempted to take the level of analysis one step further; from the analysis of individual differences to an analysis of the individual herself throughout the course of a single task.

We asked ourselves whether the participants' momentary emotional states determine their decision, and whether previous decisions and outcomes change these states.

We hypothesized that participants are either in a risk taking (high arousal) or a risk aversive (low arousal) state that determined their decisions. We also hypothesized that previous decisions and their outcomes can change the state that the participant was in. We provided insight regarding the change of the level of arousal via measurement of a physiological response, pupil size. We found that in a continuous decision making task, an analysis that considers decision making responses independently will not be able to capture the dynamic (changing) nature of participants' momentary emotional states.

As the final word; we believe that a dynamic understanding of decision making under uncertainty is essential to capture the participant's changing behavior with respect to decisions and outcomes. Such an understanding of these tasks will help categorizing the participants' behavior and their physiological responses in a better perspective than assuming that their emotional states stay the same throughout the task.

Our findings suggest that sequential decision making paradigms under uncertainty are dynamic by nature. Even when there is no learning, the participant behavior changes in time with respect to decisions as well as their outcomes. This change that relates to risk can be monitored and captured by using a simple unobtrusive measure, pupil size. We believe that including a temporal analysis of participant responses will have a positive impact on every similar study in this field.

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APPENDIX A

DOSPERT SURVEY

Original Survey (in English)

For each of the following statements, please indicate the **likelihood** that you would engage in the described activity or behavior if you were to find yourself in that situation. Provide a rating from *Extremely Unlikely* to *Extremely Likely*, using the following scale:

1	2	3	4	5	6	7
Extremely Unlikely	Moderately Unlikely	Somewhat Unlikely	Not sure	Somewhat Likely	Moderately Likely	Extremely Likely

1. Admitting that your tastes are different from those of a friend. (S)
2. Going camping in the wilderness. (R)
3. Betting a day's income at the horse races. (F/G)
4. Investing 10% of your annual income in a moderate growth mutual fund. (F/I)
5. Drinking heavily at a social function. (H/S)
6. Taking some questionable deductions on your income tax return. (E)
7. Disagreeing with an authority figure on a major issue. (S)
8. Betting a day's income at a high-stake poker game. (F/G)
9. Having an affair with a married man/woman. (E)

10. Passing off somebody else's work as your own. (E)

11. Going down a ski run that is beyond your ability. (R)

12. Investing 5% of your annual income in a very speculative stock. (F/I)

13. Going whitewater rafting at high water in the spring. (R)

14. Betting a day's income on the outcome of a sporting event (F/G)

15. Engaging in unprotected sex. (H/S)

16. Revealing a friend's secret to someone else. (E)

17. Driving a car without wearing a seat belt. (H/S)

18. Investing 10% of your annual income in a new business venture. (F/I)

19. Taking a skydiving class. (R)

20. Riding a motorcycle without a helmet. (H/S)

21. Choosing a career that you truly enjoy over a more secure one. (S)

22. Speaking your mind about an unpopular issue in a meeting at work. (S)

23. Sunbathing without sunscreen. (H/S)

24. Bungee jumping off a tall bridge. (R)

25. Piloting a small plane. (R)

26. Walking home alone at night in an unsafe area of town. (H/S)

27. Moving to a city far away from your extended family. (S)

28. Starting a new career in your mid-thirties. (S)

29. Leaving your young children alone at home while running an errand. (E)

30. Not returning a wallet you found that contains $200. (E)

Note 1. E = Ethical, F = Financial, H/S = Health/Safety, R = Recreational, and S = Social.

Note 2. These two footnotes and group definitions given in parentheses after questions are not present in the participant's copy.

Turkish Version (not validated through a norm study)

Lütfen, aşağıdaki durumların her biri için, eğer kendinizi o durumda bulsaydınız, belirtilen hareketi veya davranışı **ne ölçüde göstereceğinizi** işaretleyiniz. Anket 30 adet 7'li skala sorusundan oluşmaktadır. Her durum için, belirtilen hareket veya davranışı ne olasılıkla göstereceğinizi aşağıdaki skalaya göre işaretleyiniz:

1	2	3	4	5	6	7
Kesinlikle Hayır	Çok Düşük	Düşük	Emin Değilim	Yüksek	Çok Yüksek	Kesinlikle Evet

1. Bir arkadaşınıza karşı zevklerinizin onunkilerden farklı olduğunu dile getirmek.
2. Bir vahşi yaşam alanında kamp yapmaya gitmek.
3. Bir günlük kazancınızla at yarışı oynamak.
4. Yıllık kazancınızın %10'unu orta halli büyüyen bir fona yatırmak.
5. Sosyal bir ortamda fazla miktarda alkol almak.
6. Özel bir harcamanızı şirket harcaması olarak gösterip vergiden düşülmesini sağlamak.
7. Önemli bir konu hakkında bir büyüğünüz ya da otoritesini kabul ettiğiniz biriyle zıtlaşmak.
8. Bir günlük kazancınızı yüksek bahisli bir poker oyununa yatırmak.
9. Evli bir erkekle/kadınla ilişki yaşamak.
10. Başka birinin yaptığı bir işi kendinizin gibi göstermek.
11. Yetenek ve deneyiminizi aşan bir pistte kayak yapmak.
12. Yıllık gelirinizin %5'ini hayli spekülatif bir fona yatırmak.
13. Yüksek debili bir nehirde rafting yapmak.
14. Bir günlük kazancınızı bir spor müsabakasının sonucuna yatırmak.
15. Korunmadan cinsel ilişkiye girmek.
16. Bir arkadaşınızın sırrını başka biriyle paylaşmak.

17. Emniyet kemeri takmadan araç kullanmak.
18. Yıllık gelirinizin %10'unu yeni bir iş fırsatına yatırmak.
19. Uygulamalı hava dalışı eğitimi almak.
20. Kasksız motosiklet kullanmak.
21. Prestijli bir kariyer yerine sizi gerçekten mutlu edecek bir kariyeri seçmek.
22. İş yerinizdeki bir toplantıda sevimsiz bir konuda rahatça konuşmak.
23. Güneş kremi kullanmadan güneşlenmek.
24. Yüksek bir köprüden bungee-jumping yapmak.
25. Küçük bir uçağı uçurmak.
26. Gece vakti tekin olmayan mahallelerden evinize yürüyerek gitmek.
27. Aile ve yakın çevrenizden çok uzak bir şehre taşınmak.
28. 30'lu yaşlarınızın ortasında yeni bir kariyere başlamak.
29. Anlık bir işiniz sebebiyle çocuklarınızı evde yalnız bırakmak.
30. İçerisinde 200 TL bulduğunuz bir cüzdanı sahibine teslim etmemek / sahibini aramamak.

APPENDIX B

DOSPERT TEST RESULTS

Results of the tests with the DOSPERT scores were reported as not-significant. These test results are presented here as an appendix.

The Length of the Risk Taking State

Length of the risk taking state was calculated as the ratio of risk taking trials over all trials. Regression test results indicated that the risk taking state lengths were not significantly predicted from the Grand DOSPERT scores (averages of 5 domains); $F(21) = 3.327$, $r = .378$, ns (Table 25).

Table 25: Regression Test Results between DOSPERT Scores and Risk Taking State Lengths

ANOVA[b]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.034	1	.034	3.327	.083[a]
	Residual	.205	20	.010		
	Total	.239	21			
a. Predictors: (Constant), DOSPERT						
b. Dependent Variable: Risk Taking State Length						

The Percentage of the Pump Response

Pump response percentages were calculated as the ratio of trials with pump responses over all trials. Regression test results indicated that the pump response percentages were not significantly predicted from the Grand DOSPERT scores (averages of 5 domains); $F(21) = .265$, $r = .114$, ns (Table 26).

Table 26: Regression Test Results between DOSPERT Scores and Pump Response Percentages

ANOVA[b]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.004	1	.004	.265	.612[a]
	Residual	.294	20	.015		
	Total	.298	21			
a. Predictors: (Constant), DOSPERT						
b. Dependent Variable: Pump Percentage						

Total Score

Regression test results indicated that the participants' total scores were not significantly predicted from the Grand DOSPERT scores (averages of 5 domains); $F(21) =.035$, $r = .044$, ns (Table 27).

Table 27: Regression Test Results between DOSPERT Scores and Total Scores

ANOVA[b]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	$4.56*10^{-6}$	1	$4.56*10^{-6}$	.035	.853[a]
	Residual	$2.31*10^{-9}$	20	$1.29*10^{-8}$		
	Total	$2.32*10^{-9}$	21			
a. Predictors: (Constant), DOSPERT						
b. Dependent Variable: Total Score						

Gender

Regression test results indicated that the participants' genders were not significantly predicted from the Grand DOSPERT scores (averages of 5 domains); $F(21) = 1.367$, $r = .253$, ns (Table 28).

Table 28: Regression Test Results between DOSPERT Scores and Gender

ANOVA[b]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.340	1	.340	1.367	.256[a]
	Residual	4.978	20	.249		
	Total	5.318	21			
a. Predictors: (Constant), DOSPERT b. Dependent Variable: Gender						

CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: Taşkın, Kemal

Nationality: Turkish (TC)

Date and Place of Birth: 23 August 1981, İzmir

Marital Status: Married

Phone: +90 530 763 13 21, +49 162 215 36 74

email: kemal.taskin@enocta.com

EDUCATION

Degree	**Institution**	**Year of Graduation**
MS	METU Informatics Institute, Cognitive Sciences	2005
BS	METU Computer Engineering	2003
High School	Karşıyaka Anadolu High School, İzmir	1999

WORK EXPERIENCE

Year	**Place**	**Enrollment**
2015-Present	Enocta B2C	Software Architect and Developer
2006-2015	Enocta	Software Development Dept. Manager

2005-2006	Turkish Armed Forces	Software Project Officer
2004-2005	Enocta	Senior Software Engineer
2003-2004	The Scientific and Technological Research Council of Turkey (TÜBİTAK)	Researcher

FOREIGN LANGUAGES

Native Turkish, Advanced English, Intermediate German

VITA

Kemal Taşkın was born in İzmir on August 23, 1981. He received his B.S. degree in Computer Engineering from the Middle East Technical University in June 2003. He worked in government institutions and companies as a researcher, software developer and department manager positions since then. He continued his education in the same university, in cognitive sciences field. His main areas of interest in academics are decision making, artificial intelligence, dynamic systems and neuroscience.