EMOTIONS AND COGNITIVE WORKLOAD IN ECONOMIC DECISION PROCESSES -A NEUROIS APPROACH

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Abstract

Decision behavior may be regarded as a specific and a very important category of human behavior. Decision processes are what gives us the power to be different from each other, they are what enables us to gain charge of our own life. The influence of cognitive and emotional processes on decisions have been recently highlighted. Emotions are automatic processes, and may occur consciously or non-consciously. They constantly interplay with the conscious process of cognition, and determine the course of decision processes. In extant literature, much work remains to be done, to explore whether and how emotional and cognitive processes influence how external contexts are perceived, and how these influences manifest as behavior. This thesis is an attempt to explore these interrelationships.

In this present work, the role of external and internal influences on economic decision processes, and consequently on decision behavior, are studied. To this end, a NeuroIS method is applied, in order to measure internal processes (of emotions and cognitive workload). Research models describing these interrelationships are proposed and verified using appropriate statistical approaches. Three experimental studies are conducted and presented, in specific decision-making contexts (of financial trading, auctions, and serious games), with parameterization for external influences (such as information, gains and losses, and uncertainty) on behavior. Our results highlight the following: across participants, (1) each environmental factor potentially impacts a different internal process; (2) the direction and the extent to which these external processes impact behavior can be modelled; (3) taking personality factors into account provides further explanation on the extent of their impacts on decision behavior.

In order to conduct these experiments, the lack of a suitable experimental platform for performing NeuroIS studies was additionally recognized. Hence, as part of the thesis, Brownie, a NeuroIS platform for lab experiment, is designed and developed, using a design science approach. In addition to the experiments in this thesis, the use of the platform in other behavioral research contexts is demonstrated and evaluated.

To my parents

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Chapter 1

Introduction

> “Human behavior flows from three main sources: desire, emotion, and knowledge.
>
> PLATO (PHILOSOPHER, 427-347 BC)

Decision behavior may be regarded as a specific and a very important category of human behavior. Decision processes are what give us the power to be different from each other, they are what enable us to gain charge of our own life. There are two types of influences that may impact decision behavior (Bechara and Damasio, 2005). The first one of them - is dynamic *external* influence. In trading and auction contexts, continuous updates on prices serve as external (informational) influences. Another example of external influence in auction and group decision contexts, is the presence of other peers, and their behavior. These external influences trigger specific internal processes (namely, cognitive and emotional) in us, ultimately manifesting as behavior. For instance, information triggers cognitive thought processes, whereas aspects such as time pressure or social competition might trigger emotional processes. These two processes, namely emotional and cognitive, are categorized as the second type of influence - *internal* - on behavior. From a digital-world perspective, the loop which describes how behavior may be influenced by external and internall influences, is a fascinating one, (Bechara and Damasio, 2005, c.f. the body-loop and the as-if-body-loop), and it is this loop which we investigate further in our studies. In this spirit, this work is dedicated to studying economic decision behavior, and to understanding the interplay of affective processes (e.g., emotion and desire) and cognitive processes (e.g., knowledge and analytical reasoning), and how this interplay is affected by external factors.

This thesis contributes to research that studies the influence of emotions and cognitive workload on economic decision processes. We hence attempt to quantify, to what extent these external and internal influences impact economic decision-making, and how user interface design and user experience may be enhanced by using these results. These findings contribute to behavioral theory to better understand the interplay of cognitive and affective influences in decision-making, in settings with specific external influencers. In order to measure and study affective and cognitive processes, we adopt and follow a NeuroIS approach. NeuroIS is formally defined as the method of integrating neuroscientific and neurophysiological theories for the design of IT artefacts (Riedl et al., 2010). It has shown to be increasingly relevant in furthering the understanding of decision-making, with applications in the context of electronic markets as well (Adam et al., 2011; Dawson et al., 2011). NeuroIS methods facilitate the measurement of physiological changes accompanying the use of technology, in the form of affective and cognitive processes.

1.1 Internal processes and decision behavior

As stated earlier, influences on decision behavior may be broadly categorized as being *external*,or *internal*. To understand human decision behavior, the realm of behavioral economics has given new perspectives - moving from traditional utility theories, to factoring in both the influences of external and internal factors on decision-makers (Kahneman and Tversky, 1979; Damasio, 2003). Formally defined, internal or innate processes encompass the *cognitive* and *affective processes*, and the associated neural processes that underlie individual behavior. Affective and cognitive processes are defined in this thesis, based on the model by Walla and Panksepp (2013). At the base of this model, are (raw) affective processes, i.e., the unconscious processes which occur naturally without effort, and are accompanied by physiological changes. Second, (parsed) emotions are consequences of raw affective processing, and can be modified by the influence of higher order processes, thus giving semantic meaning to the raw affective processes. Third, is the process of cognition, which is the deliberative and conscious process occurring in the neocortical part of the brain. Cognition is hence viewed independent of raw affective processes. Based on this distinction, in the scope of this thesis, we are primarily concerned with raw affective processes - which are unconscious, and without any interpretation as an emotion - and cognitive processes - which are entirely conscious and deliberative.

The first and foremost internal process considered in this thesis is the role of affect. An affective process is defined to be unconscious, and not processed by higher cognitive functions, and accompanied by bodily changes, such as increased heart rate, a higher skin conductance response, or dilation of the pupils (Walla and Panksepp, 2013). Measuring these physiological changes is useful to unobtrusively obtain information about the internal state of a person, especially when the state is constantly changing due to the context. For instance, a sudden excitement from a calm state, or a heightened state of arousal after this sudden excitement, may be measurable and observable physiologically. To assess these changes, bio-sensors have been increasingly utilized to measure physiological activity, particularly that of affective processing, in recent literature (Fernandez et al., 2012; Astor et al., 2013a). While earlier studies have studied how affective processes (i.e. arousal levels) are varied in different economic contexts, the primary question we address in this thesis is, to what extent, and in which direction do affective processes impact decision-making. Are they a pre-requisite for decision-making such as illustrated by (Bechara and Damasio, 2005), or is the influence of affective processes on decision processes context-dependent (Shiv et al., 2005)?

In understanding the impact of affective processes, it has been highlighted in earlier literature that it is vital to consider individual differences in emotional processing capabilities (Fenton-O'Creevy et al., 2012). Whether a person "allows" emotions to influence his behavior or not, is dependent on his emotion regulation strategy (Gross and John, 2003). For instance, reappraisers (i.e., the strategy of altering a situation's meaning in a way that alters its emotional impact) have shown to maximize their utility better, whereas suppressors (i.e., the strategy of modulating the response after it has been generated) have shown to be make fewer utility maximizing decisions (Heilman et al., 2010). Hence, in addition to the direct impact of affect on decision processes, we examine whether the role of affective processes depends on individual characteristics, in particular, the emotion regulation strategies employed by a person, and if so, how do these dependencies impact decision-making.

The second internal process we study is that of deliberative and conscious processes, which is accompanied by cognitive workload (Phelps, 2006). In a typical economic decision-making process, cognitive workload is manifested when thinking about decision alternatives, factoring in several parameters, or even including others' knowledge levels, strategies and behavior. Arriving at the theoretically-expected equilibrium decision is further made difficult, in situations that require estimation of the probability of an event to occur, or in factoring in the information uncertainty associated with a context. Theory states that, whether a rational (deliberative) cognitive process is applied, or a fast (automatic) affective process takes charge, depends to a large extent on the external and business factors, including aspects of risk, uncertainty, and even time pressure (Gigerenzer and Gaissmaier, 2011; Lieberman, 2007). Hence, we examine in this thesis, how cognition impacts decision-making, and how affect and cognition interplay with each other in determining decision processes.

1.2 External influences and decision behavior

External influences may be aggregated to the notion of *environment*, i.e., the external set of circumstances that have an impact on, but are outside the control of the decision maker (Hurwicz, 1973). These encompass the entities, physical environment and events relative to which individuals must act (Damasio, 2003). Smith (1989) defined the environment as the collection of all agents' characteristics, and also the set of business factors that impact demand and supply. From the perspective of engineering and designing markets, whether a scenario is stable, or whether it contains vagaries due to external factors, matters for design (Weinhardt et al., 2003). Specifically, these external factors might induce uncertainty in price, as well as the information regarding prices available to different agents. This information uncertainty, about the true value of a price, consequently determines decision processes, individual behavior, thus ultimately impacting the overall market outcome as well. Other examples of external influences would be, probability of occurrence of an event (how probable it is, that a stock rises in value), the amount of time available to arrive at a decision, and the uncertainty associated in determining the value of a product, etc. Hence, the questions explored in this thesis are relevant from a market engineering perspective, especially in the domain of electronic markets and the design thereof.

External influences undoubtedly determine behavior to a large degree. For the purpose of this thesis, we classify the external influences to be of three types. The first one of them is *events*, i.e., circumstances which occur in nature and shape our decision processes, as defined in the context of an emotional framework for auction bidding (Adam et al., 2011). A specific type of event we consider in this work, is the financial gains or losses that occur due to several factors in a given situation. Under the assumption that an external event (gain or loss) has occurred, we focus on the influence of this event on subsequent decision processes. The second type is *known parameters*, i.e., factors which may be altered by a system designer, and whose information is also available to the decision-maker. This definition is close to the traditional definition of an institution, i.e., humanly devised constraints imposed on human interaction (North, 1987). We will examine two such known parameters: the amount of time available to arrive at a decision, or whether a user is in an individual or a group decision context. The third type of external influence we consider, is that of *unknown parameters*, i.e., factors which may not be altered by a system designer, and whose information is not (directly) available to the decision-maker, which goes back to the definition of environment by Smith (1989). An unknown parameter we study in this work, is the information uncertainty concerning a value, or uncertainty about how much others estimate a given product. The second unknown parameter, is the probability of occurrence of an event, such as how probable is it for a gain or a loss to occur. In the following, we will look into each of these external influences, and why it is important to study them, iin more detail.

Turning towards the external influences, the first influence we study, is how the experience of gains and losses might alter decision behavior (i.e., an event). In a large market setting with thousands of traders, gains and losses may be viewed upon as an external influence that impacts individual behavior, when an individual has minimal influence on overall market prices, and price formation. Under prospect theory, when faced with choices involving simple lotteries, people have been shown to behave as if maximizing an "S"-shaped value function, whose shape implies that, utility is often defined on gains and losses rather than on levels of wealth (Kahneman and Tversky, 1979). In particular, Odean (1998) showed that the experience of financial gains and losses manifests as affective reactions, and hence, is likely to distort the role of business factors and compel people to act based on affective influences. This phenomenon has been termed as the disposition effect, i.e., the tendency to hold losses too long, and to sell gains too quickly. Hence, it appears that the external influence of a financial gain or a loss, impacts decision behavior, and should be taken together with how we deal with these losses internally. These two ultimately determine whether a utility maximizing decision is reached or not. We hence involve ourselves in understanding decision behavior, given that a gain or a loss has already occurred, due to the (possible) differences in perceiving and factoring in the (emotional) impact of gains and losses on subsequent decision processes.

The second external influence we study, is a known parameter, namely, the amount of time available to arrive at a decision. The question whether there is sufficient time to think deliberatively during decision-making, or only little time to act based on an affect-based heuristic, is one that has been studied in the context of decision processes, as well as in the NeuroIS literature. Specifically, whether a person is bidding in a fast or a slow Dutch auction, has shown to lead to unexpected differences in bidding behavior, and to determine the final auction prices (Adam et al., 2012b). Time available (or the lack thereof) has also shown to reduce (or augment) the occurrence of what is called as competitive arousal (Ku et al., 2005), and to consequently impact bidding behavior. Taking this background into account, we examine the influence of available time, which is a known parameter, and its influence on economic decision processes. In the context of auctions, time available is modelled as auction dynamics (whether it is a static or a dynamic auction).

The third external influence we study, is a known parameter - that of the group context a person is placed in. Decision-makers have shown to apply different strategies, whether they are placed in an individual context, or whether they are making decisions in a group context (Peng and Hsieh, 2012). In addition, the relationship between individuals in a group is important to understand, since performance is often predicted by, for instance, whether the individual is in cooperation with others in the group, or in competition. These factors have shown to influence how the task is perceived, how much effort is put into it, and consequently how well a person tends to perform (Bolton et al., 2005). The setting (whether it is individual or group), is hence an important external factor, which influences individual decision processes to a large extent, and we study this influence in this thesis.

The final external influence we consider is an unknown parameter, namely, uncertainty in determining the true value of a product. Yin (2006) suggested that uncertainty about a product's value may arise due to dispersed information across users. Another source of uncertainty could stem regarding the trustworthiness of the seller, or the e-commerce platform that is being used. Value uncertainty reflects the degree of information available to the various users, and in an auction, it is highly relevant, since it determines the winning bid, and hence the payoff of the bidders, as well as the auctioneer. Hence, it is likely, that uncertainty about the value of a product, and to what extent people factor in this uncertainty is a key determinant of decision processes.

The next section outlines the research questions posed in this thesis, pertaining to the influence of the external and internal processes on behavior.

1.3 Research outline

Decision processes and their mechanics, are important to understand due to the possibly high economic consequences of decision processes. They underlie everyday purchasing decision processes in both private and professional contexts. Decision processes determine whether traders hold or sell an owned stock. They occur while estimating the value of a product, and deciding how much to pay for it, only to be complicated further by information about the prices estimated by others, and the uncertainty in the product itself. These various influences often occur together in nature, and to disentangle the different effects on behavior, it is vital to study them empirically. To this end the methods of experimental economics comes to the aid, by providing a structured way to study the effects of specific variables (both external and internal processes) on economic decision processes in the lab.

Figure 1.1 details the overall structure of this thesis. Currently, there exists a wide variety of software to simulate decision contexts, and to study the effects of specific economic and business factors on behavior. Before getting on with the research questions, in this work, we spend some effort in understanding, which technologies and tools are essential to carry out empirical research in the lab. "The right tool for the right job" is hence a key determinant of the ability to meet research goals. In addressing the requirements of NeuroIS and research in decision-making contexts, identifying the tools was a challenging task. In other words, there was a necessity to iteratively define and identify these requirements of a potential platform, and develop such a platform, which is not only useful to answer the research questions in this thesis, but is also useful for NeuroIS research and experimental economic researchers in general. To this end, we adopt an iterative design science method: by combining design and development, using evaluations to define further requirements, we develop an experimental platform for NeuroIS experiments [1]. The second chapter of this thesis addresses the following design objective:

- **DO: A freely available and extensible experimental platform that facilitates (i) experiments of individuals and groups, (ii) physiological measurements and time synchronization, and (iii) real-time integration of physiological data**

After addressing the design objective, we next turn to the research questions in this thesis. From the psychological front, individual differences in dealing with emotional im-

[1] Chapter 2 is joint work with Marc T.P. Adam, Verena Dorner, Ewa Lux, Marius Mueller, Jella Pfeiffer, Christof Weinhardt (Müller et al., 2014; Hariharan et al., 2015)

pacts, i.e., the emotion regulation strategy, has shown to determine the extent of influence of affective processes (Gross and John, 2003) on behavior. However, a gap in literature currently, is the understanding, whether emotion regulation strategies aid to regulate and deal with the affective impacts of experiencing losses and gains, and leads us to more utility maximizing decision-making. Hence, we aim to understand deviations from EV maximization in a trading context, by studying the direct and the moderating role of emotion regulation strategies on emotional arousal and on EV-maximizing behavior, respectively[2]. The following research question is addressed in the third chapter:

- **RQ1: In an individual context, do emotion-regulation strategies moderate the role of integral arousal on EV-maximizing behavior, particularly in dealing with the external influences of gains and losses?**

Having considered the role of emotions and emotion regulation, it is made evident that emotions are being continuously and consciously regulated, and balanced by deliberative thought processes. Electronic markets are a perfect stage for this dynamic interplay between rationality and emotions. In the next study, we attempted to quantify the experienced cognitive workload and emotional arousal, and examine how the external decision environment (i.e., the auction) moderates their impact on bidding behavior. In addition, in comparison to the previous study, which deals with individual decisions, we dealt with a group context, where group refers to the interaction with a computer agent. To this end, the following research question is addressed in the fourth chapter [3].

- **RQ2: In a group context, to what extent is the relationship between cognitive and affective processes and bid deviations determined by auction dynamics and value uncertainty?**

So far, we have studied the influence of the external decision environment (trading, and auctions), on internal processes (emotional arousal, and cognitive workload). However, both these contexts dealt with individual decision proceses, without involving the presence of other humans. While this is insightful to understand human behavior in itself, it has to be stated that performance and behavior is often modified by the group setting we are in, namely, whether it is cooperative or competitive, and how these translate to

[2]Chapter 3 is joint work with Philipp Astor, Marc T.P. Adam, and Christof Weinhardt (Hariharan et al., 2013a,b; Hariharan and Adam, 2015; Hariharan et al., 2015)

[3]Chapter 4 is joint work with Kai Fuong, Timm Teubner, Marc T.P. Adam, Christof Weinhardt (Hariharan et al., 2014, 2016)

differences in game performance. Hence, the last study of this thesis attempts to understand performance in a group context, and to study the impact of external influences & personality-related factors, on game performance. Specifically, we address the following research question in the fifth chapter [4]:

- **RQ3: In a group context, how do external influences (cooperative and competitive game playing mode), and personality-related factors (characteristics and internal processes) impact individual and group game performance?**

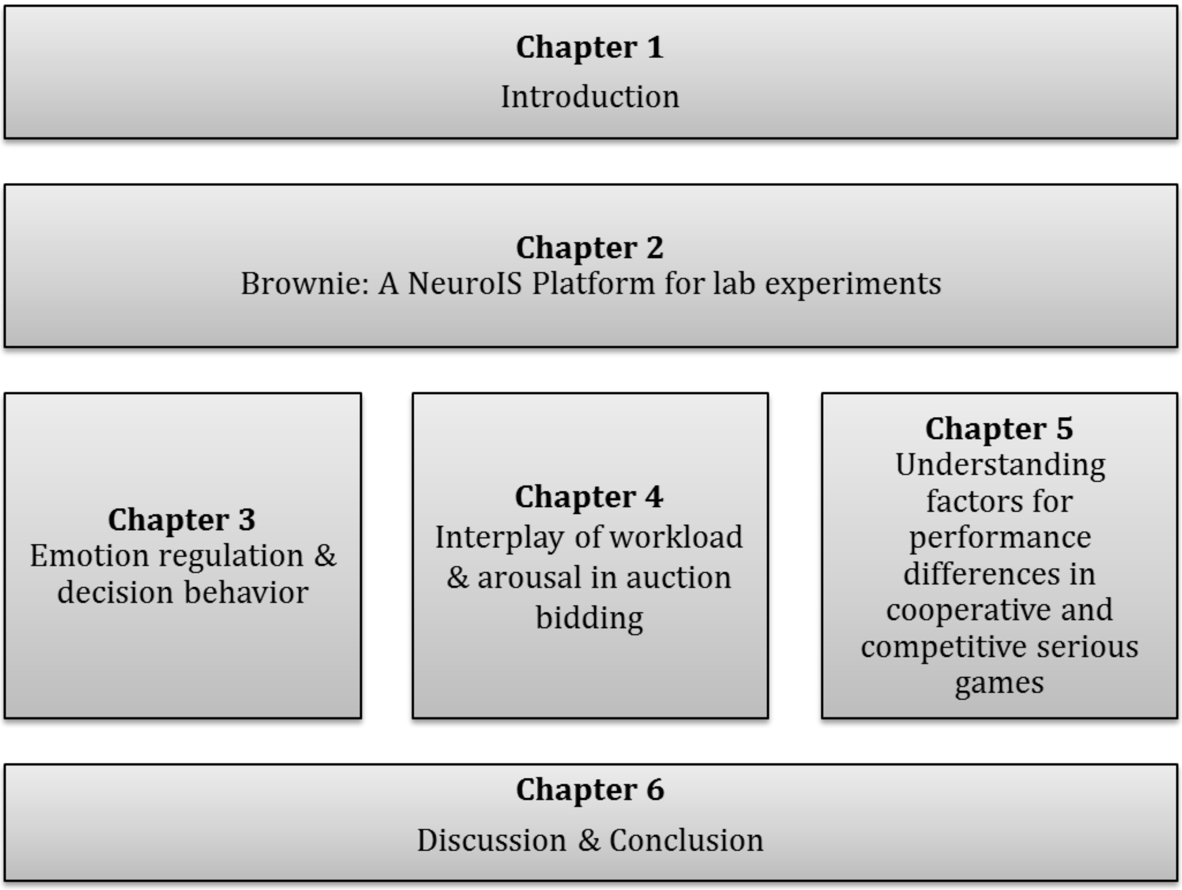

FIGURE 1.1: *Structure of this thesis*

In the words of Epictetus [5]: "We cannot control what is happening to us. But what we can control, and be aware of, is how we deal with these changes, and how these influence our decision processes and behavior." In this spirit, in the following chapters, we attempt to understand better, the external and internal influences on decision processes.

[4] Chapter 5 is joint work with Verena Dorner and Marc T.P. Adam (Hariharan et al., 2015, 2016)
[5] Greek Philosopher, 55-135 A.D.

Chapter 2

Brownie: A platform for NeuroIS experiments

> “There is a great satisfaction in building good tools for other people to use.
>
> FREEMAN DYSON, PHYSICIST AND MATHEMATICIAN, 1923-PRESENT

In recent years, built-in sensors in everyday devices have enjoyed a large amount of popularity. For instance, many mobile devices now include heart rate monitors (Apple’s iWatch, Fitbit Charge HR, or Samsung’s Gear Series) to monitor sports activities or elderly people’s health status. Other uses include giving people with disabilities greater control of their lives, e.g. by developing muscle- and brain-control interfaces (Zander and Kothe, 2011). Apart from the use of sensor data in biomedical applications, the potential of sensor data for everyday applications like e-commerce websites is attracting more and more interest. However, research on how integrating biosensor data in information systems affects IT-related behaviors and system usability is still in early stages. One of the major reasons is the complexity of implementing, conducting and interpreting (experimental) studies in the domain of Neuro Information Systems (NeuroIS). In other words, a substantial body of researchers are aiming to facilitate and enhance research in Neuro-Information-Systems (NeuroIS), and are building several tools and platforms to facilitate NeuroIS research. In the spirit of the epigraph, in this chapter, we aim at creating one such platform, which can be used by NeuroIS researchers in conducting experiments. We herewith present the various stages in creating this tool. The tool will be employed in conducting the studies in this thesis, thus demonstrating the development and use of the tool. The tool has also been used by other research teams (both internal and external) in exploring NeuroIS and non-NeuroIS research questions.

2.1 Introduction

The proliferation of built-in biosensors has made it possible to integrate biosignals as real-time system input for everyday use, such as in stress management (Riedl et al., 2013) and emotion regulation for financial trading (Djajadiningrat et al., 2009; Astor et al., 2013a). As a subfield of IS research, the area of NeuroIS builds on the advances in biosensor technology, applies neuroscience theories, methods, and tools to contribute to: (i) the development of theories that enable more accurate predictions and explanations of IT-related behaviors, and (ii) the design of IT artefacts, which positively influence technology adoption and user experience (Dimoka et al., 2011; Riedl et al., 2010, 2014). Neurophysiological data contributes to better understand NeuroIS constructs like emotions (Gregor et al., 2014), workload (Ortiz de Guinea et al., 2013), or trust (Riedl et al., 2014), which are important predictors of IT-related behavior. Specifically, NeuroIS methodologies are being applied in the domains of augmented reality (Moore et al., 2004), enterprise resource planning systems (Ortiz de Guinea and Webster, 2013), marketing and consumer behavior (Randolph, Borders, and Loe, Randolph et al.; Adam et al., 2011; Riedl et al., 2014), serious games (Li et al., 2014; Jerčić et al., 2012), recommender systems (Pfeiffer et al., 2015), technostress (Riedl, 2012), user acceptance (Kjærgaard and Jensen, 2014), among others. Beyond informing the design of IT aretefacts, NeuroIS also enables the development of neuro-adaptive information systems, i.e. "systems that recognize the physiological state of the user and that adapt, based on that information, in real-time" (Riedl et al., 2014).

The majority of NeuroIS studies have been conducted within the scope of laboratory experiments, to study individual and group IS phenomena, while establishing high levels of control (Vom Brocke and Liang, 2014; Vom Brocke et al., 2013). This need has been recognized in NeuroIS as well as in other cognate areas like behavioral economics, neuroeconomics, and affective computing (Shim et al., 2006). These novel approaches in turn require innovative and freely accessible methodological toolsets, to support researchers in developing a deeper understanding of how they enrich human-computer interaction and human decision making.

Establishing freely accessible toolsets that address researchers' needs aids the NeuroIS community and cognate areas in a number of ways. In particular, such tools can be instrumental in (1) reducing the barriers for IS researchers to engage in collaborative NeuroIS research, (2) increasing the comparability and documentation across studies, and (3) increasing the replicability of studies. Prominent examples for tools that have aided the research communities of behavioral experimental research in general and NeuroIS research in particular are the z-Tree platform by Fischbacher (2007) (which became a workhorse in experimental economics with about 6100 citations), the Ledalab platform by Benedek and Kaernbach (2010) for the analysis of electrodermal activity (about 160 citations), the ERP-Sim platform by Léger et al. (2007) (about 130 citations), the ORSEE platform by Greiner et al. (2003) for recruitment of participants (about 1600 citations), and the PhysioNet platform by Moody et al. (2001) for the analysis of physiological data (about 200 citations). But while current tools are well suited for solving issues in specific domains, we recognize a research gap for a tool that can be used across several domains, facilitates sensor-data collection, performs real-time biosignal analyses, is usable for individual and group interactive research scenarios, and finally, is open-source and fosters collaboration.

To overcome these challenges and to enable flexible integration of NeuroIS tools into experimental IS research, we identify the requirements of a solution platform. We adopt a design science approach (Peffers et al., 2007), to motivate the need for, develop a prototype, and evaluate the described IT artefact, namely, a NeuroIS tool that facilitates behavioral research. The design objective addressed in this chapter may be formulated as follows:

DO: A freely available and extensible experimental platform that facilitates (i) experiments of individuals and groups, (ii) physiological measurements and time synchronization, and (iii) real-time integration of physiological data

Identifying the requirements for, we design and introduce Brownie (behavioral Research of grOups using Web and NeuroIS Experiments). Brownie is a Java-based NeuroIS experimental platform, providing a comprehensive toolkit for a variety of experiments. We began the development of the platform three years ago, and iteratively defined the requirements and enhanced its features by means of experiments, use cases, and workshops. Brownie can be used to easily develop simple as well as complex interaction scenarios, involving individual (human-computer) and group (human-human) interactions. Brownie facilitates NeuroIS research in the lab by enabling the collection, storage, and synchronization of sensor-data events (such as electrocardiography (ECG), electrodermal activity (EDA), photoplethysmography (PPG), electro-encephalography (EEG)). In addition, Brownie is geared towards integrating real-time processing of neurophysiological measurements, thus enabling research on upcoming areas, such as neuro-adaptive systems. Brownie simplifies database storage of users' decisions and interactions. It is flexible in terms of available features for user interface (UI) development, and extensible in terms of Java libraries that may be integrated on the platform.Finally, Brownie is not limited for usage in the field of NeuroIS as it can be used for cognate domains, without involving physiological measurements as well. Its strength thus lies in settings where interaction between participants is required, as it is the case in many economic and market experiments.

This work thus contributes to the IS community by presenting the functionality, architecture, and use cases of Brownie and thus helping researchers to use Brownie for implementing NeuroIS experiments. The remainder of this chapter is organized as follows: Section 2.2 rolls out the design objective of this chapter, and identifies the need for a platform to facilitate behavioral and NeuroIS research in the lab. Section 2.3 identifies the requirements for a potential solution platform. In Section 2.4, we present the implemented platform and the architecture of Brownie. Section 2.5.1 demonstrates the application of Brownie in several use cases, followed by evaluation by means of a case study of one of these use cases. The section also presents a literature-based evaluation of Brownie, followed by a usability study amongst potential experimenters. The chapter concludes with limitations, discussions, future research and development outlook.

2.2 Problem Identification and Requirements Definition

As part of the IS research field, NeuroIS research is broadly concerned with the same objectives of investigation as the IS field in general: designing and understanding information systems and users' interactions with them. "The promise of NeuroIS is to complement existing research tools with neurophysiological tools that can provide reliable data which are difficult or impossible to obtain with traditional tools, such as self-reported or archival data" (Dimoka et al., 2010). NeuroIS shares an interest in understanding and improving human-computer interaction with cognate areas like psychology and behavioral economics. NeuroIS also faces the difficulties that arise in studying such questions, in particular the potential complexity of the interaction scenario with respect to participant, situation, and system-specific factors that might confound study results. For NeuroIS, the problem is further compounded by the difficulties inherent in measuring and processing several modalities simultaneously, as well as spatial and temporal resolution in measurements (Riedl and Léger, 2016). These aspects require the development of controlled experiments to understand system design and its effects on behavior. To this end, we formulate the need for experimentation in human-computer interaction based systems, as a central problem faced by NeuroIS researchers (Gregor et al., 2014; Ortiz de Guinea et al., 2013). Hence, in this chapter, we address this central problem by defining the scope of a solution platform, providing a solution artefact, and evaluate the platform for this problem space. To build and evaluate Brownie, we adopted the steps for a design science methodology as outlined by Peffers et al. (2007).

In order to define the scope of Brownie, we first identified the platforms used by experimental laboratories in universities around the world (behavioral, with and without sensor data) by emailing these laboratories and asking which platform(s) they used regularly for their behavioral experiments (NeuroIS and non-NeuroIS experiments). 46 laboratories around the world were contacted, of which 17 replied and a few provided information about the most commonly used platform features. We summarized the commonly used platforms in Figure 2.1 (Y-axis in Figure 2.1). For the requirement list (X-axis in Figure 2.1), we formulated requirements based on common features of the above list of candidate platforms for NeuroIS experiments by surveying features of these platforms from their manuals, and/or website information. Since the platforms comprised a wide range of features, we categorized them into four broad requirement categories (Individual and Group Interaction, Biosensors, Technical Requirements, Auxiliary Requirements), with related requirements in each category. Figure 2.1 indicates which requirements are satisfied by each surveyed platform. A literature review of NeuroIS studies (see Evaluation section) added two requirements to our list, integration of questionnaires and of multimedia. A number of auxiliary requirements (such as open source, common programming language, linking to a database, etc.) were formulated based on informal discussions with NeuroIS scholars at conferences and workshops. The four requirement categories and the requirement list were circulated among and discussed with scholars of the NeuroIS and cognate domains at several workshops; notably the NeuroIS Gmunden Retreat, 2014, attended by eminent NeuroIS scholars, who confirmed that these requirements indeed represented common requirements, and commonly faced issues while implementing NeuroIS experiments.

2.3 Requirements of Solution

2.3.1 R1: Group & individual interactions

Experimental methods can simulate a wide variety of contexts in which to study user behavior. A large part of experimental research in IS and management settings is devoted to studying decision-making and behavior of the involved users. Fischbacher (2007) noted that experiments necessitate features that involve messages from multiple users, which are managed by a central entity (hence mimicking client-server architecture). In addition, features to facilitate direct communication between users (such as trade negotiations) are required. Although existing experimental platforms provide capabilities towards this end, most of them are limited in ways that compromise their usability for NeuroIS research. For instance, as stated by the developer of z-Tree (Fischbacher, 2007), the most notable limitation of their platform concerns the timing of screen presentations. Since the server program controls the timing, delays occur before a screen presentation triggered by the server, is actually displayed at the client program. These delays are in the range of tenths of seconds, which are generally irrelevant for purely economic experiments but can be problematic for psychologically oriented experiments, specifically those involving neurophysiological measurements. A second limitation of z-Tree is the lack of interfaces to connect to external hardware and for presenting types of stimuli beyond those included in the z-Tree platform.

From the NeuroIS perspective, researchers are often interested in the kind of activity the user is pursuing (such as processing information, performing a cognitively demanding task, or making an important financial decision). NeuroIS experiments study the impact of the context on latent variables, such as emotions, workload, attention or focus-levels, formally termed as IS constructs (Nunnally and Bernstein, 1994). A precise synchronization between the task at hand and the sensor data being measured is therefore necessary. This can be achieved by means of suitable hardware or software events, to synchronize with the user decisions and corresponding timestamps. However, a majority of the existing platforms function mainly as stimulus delivery interfaces, and as control programs to manage the experiment flow (for cognitive and neurophysiological studies), and need additional programming effort to synchronize user events with sensor data. For instance, PsychoPy (Peirce, 2007) is a platform that allows the presentation of stimuli and collection of data for a wide range of neuroscience, psychology and psychophysics experiments. Psychotoolbox (Brainard, 1997) is used to measure a variety of neurophysiological thresholds, to display specialized stimuli for functional MRI and electrophysiological experiments, or to study categorization, perceptual learning, visual search, and visual object recognition tasks. All these activities thus involve stimulus presentation and human-computer interaction, or group interaction (inter-client interaction, or messages coordinated by a server). Considering the above examples, we formulate the facilitation of individual interaction (R1a), and the facilitation of group interaction (R1b) as the first requirement to be fulfilled in a NeuroIS platform.

2.3.2 R2: Biosignals

Employing biosignal data using sensors is an emerging method in assessing a user's state (such as emotions, cognitive level, focus level, relaxation state), in understanding human behavior, and in building decision support systems (Djamasbi et al., 2008). Domains such as wearable and affective computing focus on the utilization of biosignals in gaining accurate information about the statistics of a user (Shim et al., 2006). For instance: (i) heart rate data can be an indicator for the amount of stress, whether a person is emotionally aroused, or is experiencing positive or negative emotions (Astor et al., 2013; Ortiz de Guinea et al., 2013); (ii) skin conductance response can be used to measure the level of arousal (Adam et al., 2015; Minas et al., 2014), or stress (Riedl et al., 2013); (iii) electroencephalography (EEG) can be used to track electrical activities on the scalp and cortical layers and to measure which regions of the brain are most active during an activity (Gregor et al., 2014; Ortiz de Guinea et al., 2013; Kuan et al., 2014); (iv) electromyography (EMG) can be used to measure the electrical activities of the skeletal muscles to examine the subject's activation level and responses to stimuli (Schaaff et al., 2012; Minas et al., 2014) (v) eye tracking can be used to measure the movement and the area of focus, and data on fixation, gaze and saccade can be used to understand the subject's reactions while viewing an interface or performing a search task (Pfeiffer et al., 2014; Léger et al., 2014); (vi) photoplethysmogram (PPG) can be used to detect activity of the sympathetic system through changes in intravascular blood volume (Nogueira et al., 2014); (vii) in addition to the physiological methods above, brain imaging techniques, such as functional magnetic resonance imaging (fMRI) and near-infrared spectroscopy (NIRS) can be used to determine neural activity of specific constructs, such as internet adoption (Dimoka et al., 2011); and trust (Loos et al., 2010).

Incorporating sensor data in experiments demands a wide range of technical requirements. The first and foremost is the method to acquire and store data from different sensor modalities. Having different sensor modalities implies multiple sources for time references, which makes synchronization among hardware a non-trivial problem (due to delays and time-drifts). In addition, the sensor data needs to be synchronized with the current experimental data (such as clicks and information processing events), either by means of hardware triggers during the experiment, or by offline processing. The second requirement is the time resolution for sampling. For instance, HR and EEG require measurement in the precision of milliseconds, as well as the ability to handle voluminous data from a large number of channels (possibly ranging from 8-128) (Ortiz de Guinea et al., 2014). While it might not be feasible to transmit this high a volume of data to a database server directly, the platform should enable storage on each client as raw signals.

Today only a small number of experimental platforms offer these capabilities. For instance, Presentation and E-Prime (Schneider et al., 2002) support single, parallel and serial port communication and logging of experimental events. Presentation was built specifically for accurate stimulus delivery and event logging. It can receive eye tracking data and produce gaze-dependent stimuli and monitor pulse-triggered counters. Inquisit (Draine, 1998) is another platform that supports parallel port integration and could facilitate adding sensor triggers. Stim2 can be integrated with fMRI, EEG, and neuro-imaging techniques, and interfaces seamlessly with specific hardware (such as CURRY 7 and SCAN), as well as specific amplifiers (such as SynAmps2, SynAmps RT, or NuAmps). A comprehensive list is provided in Figure2.1.

Platform	Year of latest version	Individuals (R1a)	Groups (R1b)	Biosignals (R2a)	Signal quality checks (R2b)	Real-time signal processing (R2c)	Support research on websites (R3a)	Flexibility of data logging (R3b)	Common programming language (R3c)	Extensibility (R3d)	Multimedia (R3e)	Open source (R4a)	Tutorials & support (R4b)	Redistribution & replication (R4c)	Questionnaires (R4d)
BoXS (1)	2013	•	•				•				•	•	•	•	•
ConG (2)	2013	•	•						•	•	•	•	•	•	
DirectRT (3)	2014	•		•				•			•		•		•
EconPort (4)	2006	•	•				•						•	•	
E-Prime (5)	2008	•		•	•						•		•		
Inquisit (6)	2014	•		•			•				•		•		•
MediaLab (7)	2014	•									•		•		•
Presentation	2014	•		•	•		•	•		•	•		•		
PsychoPy (8)	2014	•		•					•	•	•	•	•	•	
Psychtoolbox (9)	2013	•		•									•	•	
Regate	2009	•	•										•	•	•
Seaweed	2011	•	•				•	•	•		•			•	
SoPHIE	2014	•	•				•				•		•	•	•
STIM2	2014	•		•							•				
Superlab	2013	•		•	•						•		•		
VeconLab (10)	2014	•	•				•							•	
z-Tree (11)	2013	•	•					•			•		•	•	•
Brownie	2016	•	•	•	•	•	•	•	•	•	•	•	•	•	•
		Requirement 1 Individuals & Group		Requirement 2 Biosignals			Requirement 3 Technical Requirements					Requirement 4 Auxiliary Requirments			

FIGURE 2.1: *Requirements met by current experimental platforms*

To summarize, some of the existing platforms support event logging, and several platforms facilitate neurophysiological measurements with single-user stimuli-based experiments. However, these platforms require additional effort to integrate the stimuli with the events, or to conduct experiments on groups. To specify an event trigger, these platforms permit modifications, but at the cost of additional effort from the experimenter. Hence, we formulate our second requirement (R2a) as the ability to store uni- and multimodal sensor data, and temporally synchronize these data with the various events in the experiments, in a uniform and ready-to-analyze format. A corollary of this requirement (R2b) is the ability to perform signal quality checks, to check whether sensors are connected, and whether data is being continuously stored.

An emerging requirement of NeuroIS research is the ability to integrate real-time processing of biosignals, and design systems based on this information. User input in the form of real-time biosignal data is used to adapt the system response, or system design, in real-time according to the cognitive or affective state of the user (cf. Strategy 3, Vom Brocke et al. (2013)). As stated in the NeuroIS research agenda by Riedl (2012), p.44, "Design science researchers could contribute to the development of information systems, which use biosignals as real-time system input in order to make human-computer interaction less stressful, and hence more convenient, enjoyable, and effective." These systems have been termed as "neuro-adaptive" (Riedl et al., 2014), and they are developed with the aim of improving user experience or helping the user achieve certain goals. One specific example of a neuro-adaptive system feature is the live-biofeedback, which informs users (based on their biosignals processed in real time) about their current internal state. Live-biofeedback is used, for instance, in serious games and technology-enhanced learning environments (Astor et al., 2013a; Ouwerkerk et al., 2013). In summary, neuro-adaptive systems mandate the need to integrate real-time signal processing features in an experimental platform. To this end, we formulate R2c as the ability to incorporate features for real-time processing of sensor data, in order to design neuro-adaptive systems (e.g. interface adaptation, interventions, live-biofeedback) for experimentation.

2.3.3 R3: Technical Requirements

We next identify a list of general technical requirements that are common to the majority of IS experiments, irrespective of whether they include elements of NeuroIS research, or not. Existing platforms for building experiments provide the possibility of conducting experiments on websites or modified HTML pages. Of the platforms surveyed, BoxS

(Seithe, 2012), Presentation, Inquisit, Veconlab (Bostian and Holt, 2013), EconPort (Cox and Swarthout, 2005) provide the ability to conduct experiments on specific websites and HTML pages. While it might not be possible to conduct experiments involving biosensors without inviting people to the lab, it should still be feasible to conduct experiments to study user behavior while browsing website content or making buy/sell decisions on e-commerce platforms. Experiments which study specific Internet websites can then be conducted in the lab, along with logging of physiological data, or users' click and search patterns on websites. Based on the above, we formulate R3a as the ability to conduct IS experiments on websites in a controlled lab environment.

Tracking and logging of user data and activities is an important element in analyzing user behavior. The problem with current storage methods is that platforms store the experimental data in proprietary file formats, in MS Excel or text files with their own data format. The effort for converting these outputs to convenient storage formats is potentially high. One solution is storing the experimental data as a schema, which simplifies experimenters' querying, data management, and analysis needs. To this end, we formulate R3b as the ability to provide easy data storage methods for experimenters.

Another general technical requirement across platforms is the ease-of-use in implementing an experiment. Experimental platforms may provide the experimenter with one or several of three options on how to implement an experiment. The first option is providing an interface to develop an experiment with drag-and-drop or point-and-click methods. While the programming overhead of experimenters is reduced in such platforms, the available set of functions are predefined, making it difficult, or even impossible to create advanced scenarios. The second option is providing a proprietary programming or scripting language which the experimenter must learn and apply to develop an experiment. This enables the development of complex experiments, but at a high developmental cost. For instance, platforms such as BoxS (Seithe, 2012) and z-Tree (Fischbacher, 2007) have their own programming scripts and methods which are often less well-defined than standard programming languages such as C# or Java. As stated by the author of z-Tree (Fischbacher, 2007), although the programming language is sufficiently general for implementing any kind of interaction, programming can be unnecessarily complicated in some cases, since z-Tree neither knows procedures nor complex data types. The third and final option is the use of commonly used programming languages, such as C# or Java. These languages allow for object oriented programming and for extension via specific libraries. It also simplifies the process of instruction and of obtaining support in case of issues. Furthermore, any prior knowledge of the common programming language would expedite the effort required and the skills acquired by the experimenter are transferable beyond programming the experiment. To this end, we formulate R3c as the ability to program an experiment with a commonly used programming language, as well as the ability to implement complex procedures, interfaces and interactive use cases in the lab.

Interlinked with the previous requirement of a common programming language, is the scalability and extensibility aspect of the platform. While most of the platforms surveyed in Figure 2.1 enable hardware support, they are not extensible or scalable to be combined with other devices, such as mobile platforms, and do not have a ready-to-use API to incorporate customized analysis modules for each sensor. We formulate R3d as the ability to extend the platform by means of available libraries, possibly for hardware, UI, and analysis requirements.

Finally, in order to measure the underlying physiology, stimuli have been provided in the form of text (Minas et al., 2014), images (Gregor et al., 2014; Riedl et al., 2014), sounds (Jerčić et al., 2012), or videos (Nogueira et al., 2014). Based on the above, we formulate R3e as the ability to incorporate various multimedia elements as stimuli in experiment interfaces.

2.3.4 R4: Auxiliary Requirements

An important aspect of platform usage is the license model adopted. A survey of existing platforms shows two kinds of distribution models: either they are available as open-source (available for free, modifiable in some cases, and primarily experimental platforms developed by researchers), or are distributed at a fee (not always modifiable and primarily experimental platforms developed by companies). Being open-source implies that the source code of the platform is available, and the platform is extensible by users and developers of the platform. We formulate R4a as the need for a NeuroIS experimental platform to be distributed open source, and free-of-charge.

In order to facilitate the ease-of-use and the continuous usage of a platform, another key requirement is providing a sufficient quantity of tutorials and use cases, as well as documentation and support by means of issue trackers or forums. These methods will enable good understanding of the platform, and also encourage discussions for the usage and extensibility of the platform. To this end, we formulate R4b as the requirement to provide a sufficient quantity of tutorials, documentation and support methods for a solution platform.

Finally, replicability and reusability of scientific research is an essential requirement for experimental economics (Friedman and Sunder, 1994), and in the realm of NeuroIS as well. To this end, we formulate R4c as the ability to incorporate existing use cases and implementations in new experiments, and to facilitate easy distribution and replication. This completes the list of requirements that a platform which facilitates NeuroIS research should fulfill. The above five requirements are summarized in Figure 2.1 which gives an overview about which of the surveyed platforms meets which requirement.

Collecting additional information about participants is a basic requirement of virtually all NeuroIS experiments. This includes assessment of additional data such as demographics, specific personality traits, or to record participants' perceptions during the experiment. Based on the above, we formulate R4d as the ability to incorporate questionnaires in a controlled lab environment.

2.4 Design and Development

The following section provides an overview of Brownie and the implemented architecture, and how its design reflects the above enlisted requirements. The motivation for developing Brownie emerged when the authors became aware of the growing complexity and technological challenges in conducting NeuroIS experiments, particularly since current platforms were limited in terms of extensibility, group interaction, and biosignal integration. Hence, a staged plan was envisioned to iteratively design a platform that would address those needs. This section outlines the iterative problem-solving process used to design and develop Brownie. A design as a search process approach was applied to decompose the complexity of developing a platform for laboratory experiments in the domain of NeuroIS into sub-problems, as recommended by Peffers et al. (2007) and von Alan et al. (2004). These sub-problems are represented by the requirements R1 to R4, which were addressed in three main iterations of design and development. Six use cases (i.e. experiments by internal and external researchers) guided the design and development process: to demonstrate the technical feasibility of the requirements, and evaluate the solution IS artefacts developed in each iteration.

2.4.1 Iteration 1: Basic Client-Server Architecture

Within the first iteration, Brownie's core client-server structure was implemented. This first implementation featured individual (R1a) and group (R1b) interactions. Brownie is Java-based (R3c), includes flexible data logging (R3b), and its layered architecture retains modularity and hence extensibility (R3d) while abstracting functionality. Java was chosen as the language of implementation, since it is platform independent, and is supported on several operating systems. Java is also widely used for web applications, enterprise software, and e-commerce solutions. Finally Java is the preferred choice of language in the case of extensions to mobile development, due to its compatibility with the Android system.

The architecture components can be classified along two dimensions: (i) whether they are part of the client or the server side, and (ii) whether they belong to the built-in or the customizable tier. In order to ensure encapsulation and information hiding, the platform is separated into a built-in tier, forming core of the platform, and a customizable tier for experimenters. The built-in tier is ready-to-use, and requires no alterations when implementing an experiment. A visualization of the built-in tier is given in Figure 2.2. The customizable tier, on the other hand, makes it possible to implement new experiments. Experimenters can specify user interfaces for clients, grouping rules for subjects in various periods, assign roles to clients, and customize the experimental flow. Exemplary experiments are distributed with the source code in order to increase the ease of use for first-time Brownie users.

According to design as a search process method (Peffers et al., 2007; von Alan et al., 2004), each iteration of the creative and heuristic problem solving process must produce a representation of an artefact that can be demonstrated. With respect to this first iteration of the design and development process of Brownie, artefacts were created for two standard decision scenarios: Trust Game (Riedl et al., 2014) and Ultimatum Game (Joe and Lin, 2008; Loewenstein, 2001). Both games were used to confirm the operability of Brownie's basic architecture. The games incorporated basic solutions for role management, grouping of subjects, and error and exception handling. Demonstration and discussion of these artefacts revealed several ways in which the platform needed to be adapted for advanced experimentation, which we addressed at the end of this iteration. For instance, the Ultimatum Game has two roles and a role matching requirement, but other experiments do not necessarily require this step - hence, a default single role matcher assigning all subjects to the same role throughout an experiment was implemented. Custom and experiment-specific role matching methods were also facilitated, by means of abstract classes. Similarly, general scenarios for grouping were identified (such as partner matching, random matching, perfect stranger matching, etc.) and implemented.

2.4.2 Iteration 2: Integrating Sensors for Biosignal Acquisition

The second iteration addressed the acquisition of biosignals (R2a), including signal quality checks (R2b) and real-time processing of biosignals data (R2c). The biosensor management layer facilitates the setting up, connection of, and recording of biosensor data via Brownie. For this purpose, a standardized biosensor interface with basic functions such as starting/stopping recording, and specifying locations for saving physiological data, was incorporated into Brownie. The standardized interface can be extended for specifying and configuring sensor-specific properties (such as sampling frequency, hardware connectivity information for parallel port or Bluetooth properties).

Currently, implementations for recording ECG, EDA, PPG, EEG and eye-tracking data have been completed, as well as recording of webcam data. The generic signal processing layer of Brownie facilitates, for instance, real-time heart rate analysis for providing live-biofeedback. The modularity of the biosensor tier allows the implementation of new real-time monitoring and analyses methods (i.e. filtering methods, processing algorithms, and post-processing algorithms).

Data synchronization is addressed in two different ways: the first way is where the recording of all biosensor modalities are integrated into Brownie. Here, data is recorded on one device (i.e. sensor associated with one experimental computer), all data is recorded and timestamped using the same clock. Hence, there is no post-hoc synchronization necessary. The second way is where at least one biosensor modality is not recorded directly within Brownie but recorded externally. Here, Brownie is used to record the behavioral data of the experiment and simultaneously acts as a marker signal emitter for all connected biosensors (Hariharan et al., 2014). The marker signals can then be used for post-processing synchronization of one or more modalities. In addition to those two ways, timestamps for experiment events are always recorded with server and client time in order to enable post-hoc synchronization of multiple clients with the server time. These data synchronization capabilities are within the requirements raised in the established NeuroIS guidelines by Dimoka et al. (2010) and Léger et al. (2014), e.g., simultaneously obtaining data from different sources and providing a marker signal emitter functionality. In order to demonstrate the operability of the second iteration artefact, namely the biosensor tier, the experimenters conducted three experiments 1, 2, and 3 (Table 2.1). The first two experiments involved collecting large amounts of data (e.g. up to two hours of measurement for 9 clients at a sample rate of 1000 Hz with three different sensors simultaneously), while experiment 3 included real-time signal processing. All three experiments verified the feasibility of collecting physiological data using Brownie. In this phase, challenges faced were with respect to the following: 1) Bluetooth driver compatibility, 2) Java versioning and DLL (Dynamic Link Library) compatibility with various operating systems and sensor devices, and 3) identifying processing speed requirements for real-time signal processing. These challenges were later identified and accounted for prior to the experiment setup, and appropriate solutions were integrated in Brownie.

2.4.3 Iteration 3: Preparation for Open-Source Usage

In the third iteration, Brownie and its support landscape were prepared for open-source use within the NeuroIS community. This includes open-source distribution (R3b), a support infrastructure of instructions, tutorials and exemplary experiments (R4b), as well as redistribution and replication (R4c) of Brownie and implemented experiments. In addition, the third iteration addressed further requirements identified in our literature review (see Evaluation section) and in discussions with other experimenters (see Problem identification and requirement definition section) as well as in iterations 1 and 2, such as support for website research (R3a), integration of multimedia content (R3e), and integration of questionnaires (R4d).

Brownie is fully open source and licensed under the Apache 2.0 open source license with the added requirement of a citation in case of academic use. The support infrastructure includes a wiki with information about Brownie's architecture, basic usage instructions, and a FAQ section. These are complemented by a number of video tutorials that demonstrate how to set up existing experiments as well as how to implement a new experiment on Brownie. Other video tutorials address specific questions commonly asked by experimenters (e.g., how to install JWindow Builder, how data logging on Brownie works, how to match subjects to different treatments). With respect to redistribution, the database engine PL/SQL proved difficult to install separately. To reduce this step, we switched to the database engine H2, to create a schema dynamically, without requiring separate creation by the experimenter. Users are now able to add new values to be stored in the database with minimal recreation efforts. Another step towards facilitating the redistribution and replicability of experiments was making Brownie available on Bitbucket, and giving all experimenters the opportunity to share their experimental code in the Bitbucket repository.

The result of the third iteration, a software artefact including its documentation and support infrastructure, was tested in use cases 4, 5 and 6 (Table 2.1). The experiments described in these use cases were created by external experimenters based on the documentation and support material.

2.4.4 Architecture Overview

In order to retain modularity, while abstracting functionality, we adopt a layered architecture for Brownie. Components of Brownie are segmented along two dimensions: i) whether they are used at the server or on the client side, denoted within each component, and ii) whether they are part of the built-in or the customizable tier. A detailed architecture of the platform is given in Figure 2.2.

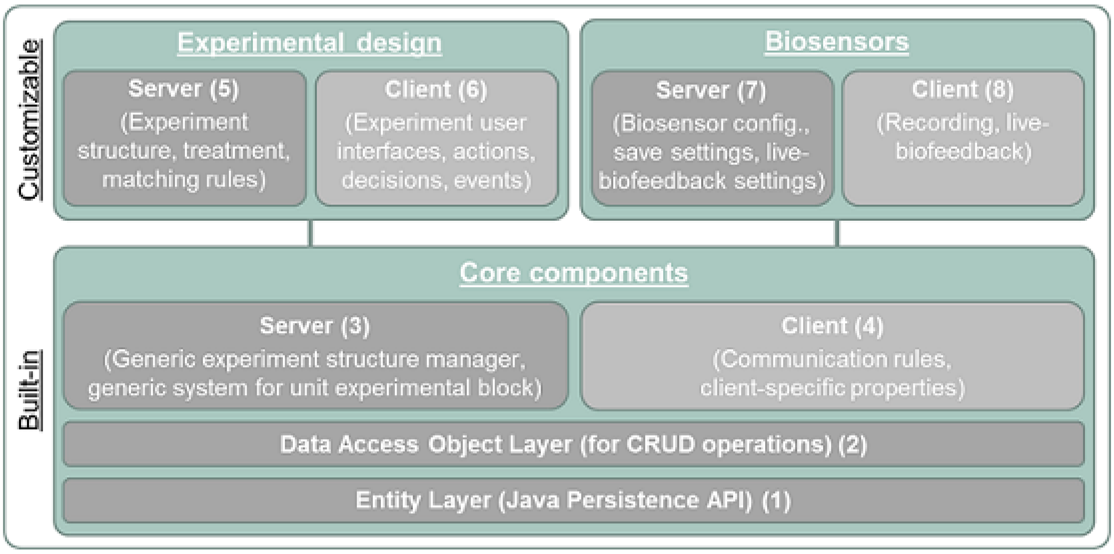

FIGURE 2.2: *Platform Architecture*

2.4.5 Built-in Tier

The built-in tier is the stable core of the platform. It is ready-to-use, and requires possibly no (or minimal) alterations while designing an experiment. The built-in tier is composed of four layers (i) the entity layer - or the object relation mapping layer; (ii) the data access object (DAO) layer - or the abstraction layer to access entity objects; (iii) the generic server - encompassing functionalities of server; and (iv) the generic client - containing functionalities to define behavior of clients. The first two layers can be modified to specify changes in the schema, or to obtain different kinds of information from the schema. In addition, the generic server and client layers can be used to manage the structure and procedure of an experiment on the server side, and the communication rules and client-specific properties on the client side. Details about the treatments (interfaces associated with the treatment), sessions (session date, cohort size, membership and matching rules), and within each session, the experiment sequence information (number of periods, pauses, etc.) can be specified on the UI. A visualization of the built-in tier is given in Figure 2.3, and the corresponding Java projects are described in Figure 2.4.

2.4.6 Customizable Experimental Tier

The customizable experimental tier is a separate Java project that facilitates implementation of new experiments. Each experiment thus consists of a client and a server side, with the former implementing client screens, and the latter consisting of an implementation of the server-side classes (Institution and Environment, Refer to wiki article on Description of architecture). Client screens can be developed using Java Swing, thus enabling access to the extensive UI capabilities and support that Java provides. This aspect of the architecture also facilitates portability to be used on any device that supports Java. For instance, controlled laboratory experiments of specific websites could be run by integrating the BrowserObject in a Java applet (thus allowing NeuroIS experiments with websites). Another instance, is that the experiment can be conducted on different mobile devices that support Java applets. The platform is distributed with a working demonstration of the Ultimatum Game, a live-biofeedback experiment, and a browser experiment. Source codes of the experiments in this document, are available upon request.

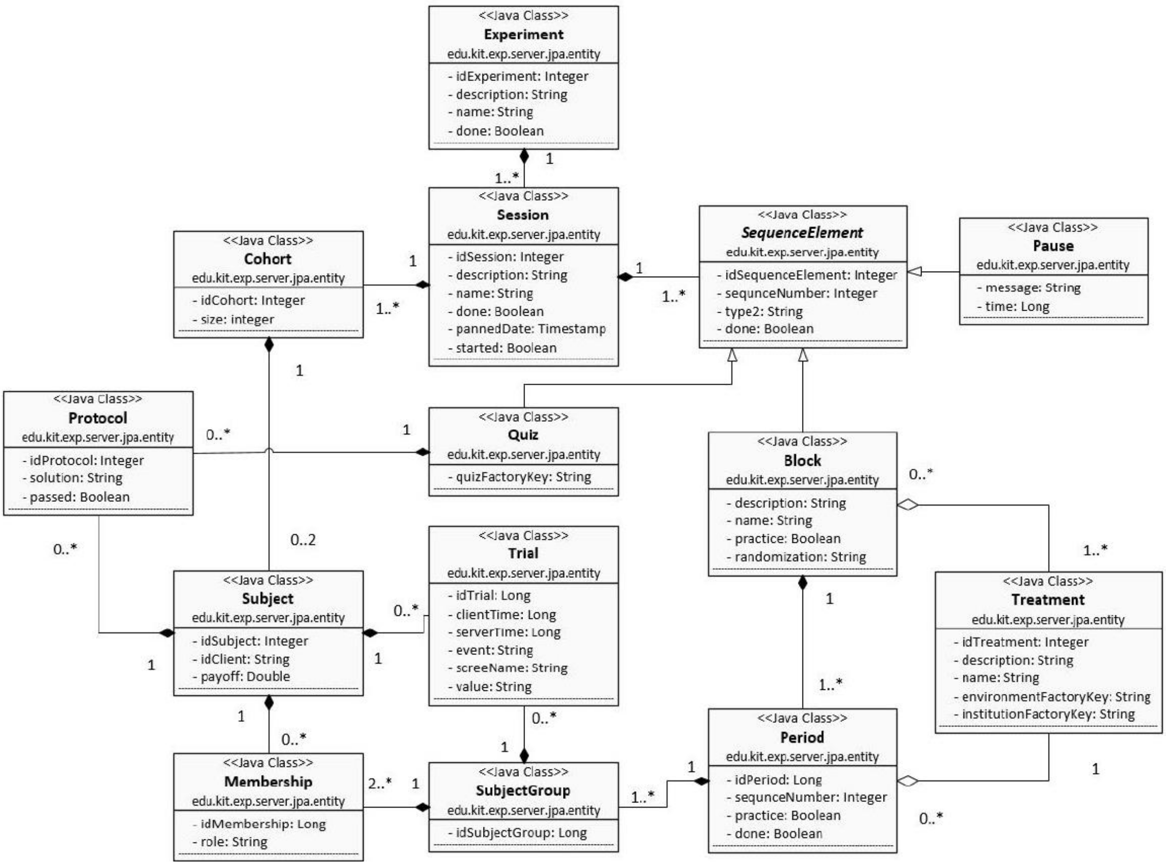

FIGURE 2.3: *Entity Diagram*

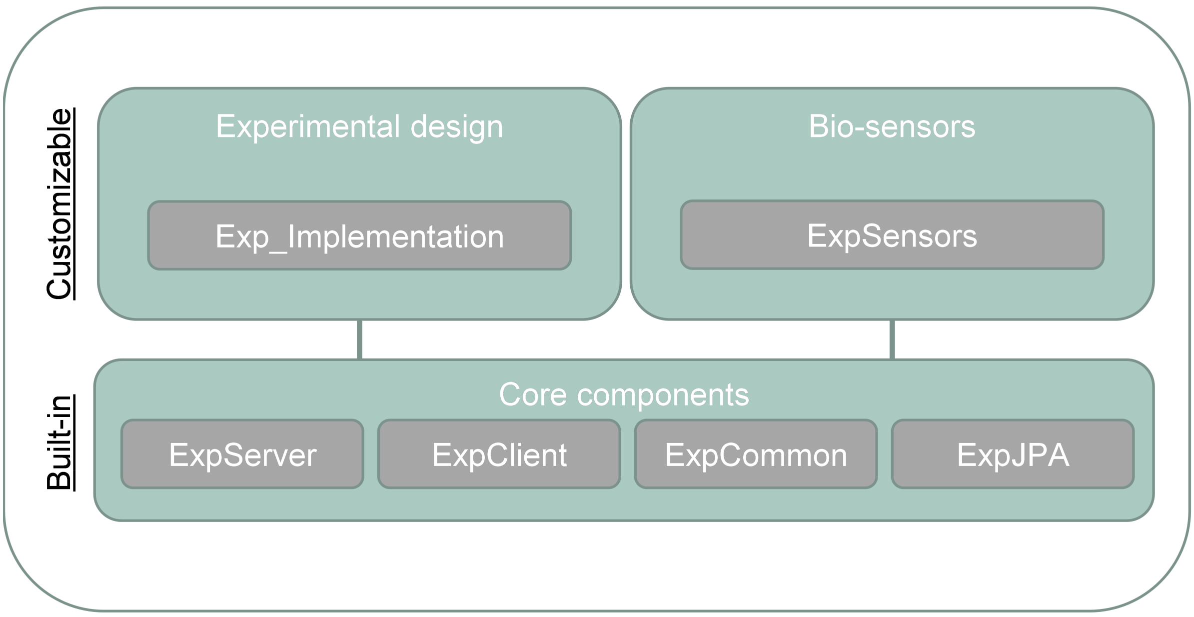

FIGURE 2.4: *Project Structure*

2.4.7 Customizable Biosensor Tier

The customizable biosensor tier consists of the sensor management and the live-biofeedback layer (as a category of neuro-adaptive system). The sensor management layer facilitates the setting up, connection and recording of sensor data via the experimental platform. Currently, implementations for recording ECG, EDA, PPG, and EEG data are available. In addition, the generic sensor recording layer of Brownie facilitates extension to use other biosensors, depending on the individual requirement of the experiment. Hence, it is possible to customize Brownie to use upcoming sensor technologies for experiments. Also, the biosensor tier is integrated with a live-biofeedback module combined with the sensor-analysis framework, xAffect, and performs real-time monitoring and analysis of heart rate and skin conductance data. Brownie hence facilitates integrating existing live-biofeedback libraries for experiments as well as implementing new real-time monitoring and analysis methods (i.e., filtering methods, processing algorithms, and post-processing algorithms).

2.5 Evaluation

2.5.1 Evaluation by means of demonstrations and use cases

In order to evaluate Brownie, we adopt a combination of evaluation methods as specified in Peffers et al. (2007): (i) an evaluation to confirm the solutions' capability to meet the specified requirements by means of observational methods (through case studies and scenarios in a business or research environment), (ii) an evaluation to identify benefits and problems in the solution, by means of descriptive methods with respect to the artefact's utility, and (iii) an evaluation to demonstrate quality and efficiency of the platform using well-executed evaluation plans, by means of descriptive methods.

The above three evaluation methods were iterated twice, once internally (by the developers of the platform), and once externally, by other experimenters. The first evaluation of Brownie illustrates the platform's use in two auction experiments (Expt. 1 and Expt. 2 in Figure 2.5). With Experiment 1, the capability of Brownie to meet the following requirements was confirmed: R1a, R1b, R2a, R3b, and R3c, R3e, R4d. With Experiment 2, Brownie demonstrated ability to fulfill requirements R1a, R2a, R3b, R3c, R3d, R3e, and

R4d. The first iteration included observational and confirmatory evaluation by the developers of the platform. In order to meet R3a, a prototype of a browser experiment was made available, which can be extended and used in an experimental setting. Brownie is distributed via Bitbucket, a repository for code sharing, which experimenters can download by requesting access to the repository, hence fulfilling R4a. R4b is achieved by adding documentations and discussing issues on Github, hence serving as a distribution, learning and discussion forum for the platform. Finally, R4c is facilitated by the use of Eclipse's Window Builder plugin, which allows for easy creation of GUI's using drag-and-drop methods on Swing.

The second evaluation iteration was carried out by presenting the platform to members of two departments at the Karlsruhe Institute of Technology. These members conducted ten different experiments with Brownie (Expt. 3 to 10 in Figures 2.5 and 2.6). The demonstration of Brownie followed an iterative process that involved demonstration to real experimenters as well as testing with student assistants. Feedback from experimenters was incorporated as features, to enhance the existing functionalities of the platform. As proposed by Peffers et al. (2007), this evaluation, based on the experimenters' experiences, contains a comparison of the initial objectives with the actual requirements of the artefact (Table 2.1).

TABLE 2.1: *Evaluation of objectives with implemented experiments on Brownie*

		Internal		**External**							
Requirement	Description	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 5	Ex. 6	Ex. 7	Ex. 8	Ex. 9	Ex. 10
R1a	Human-Computer Interaction	x	x	x	x	x	x				x
R1b	Group Interaction	x		x	x	x	x	x	x	x	x
R2a	Storage of Biosensor Data	x	x	x			x		x	x	
R2b	Signal Quality Checks			x			x		x	x	
R2c	Real-time processing			x						x	
R3a	Browser Experiments								x		
R3b	Flexibility of logging	x	x	x	x	x	x	x	x	x	x
R3c	Common language	x	x	x	x	x	x				x
R3d	Platform Extension (e.g. by Java Libraries)		x	x		x	x			x	x
R3e	Multimedia	x	x	x			x	x	x	x	x
R4a	Open Source			x	x	x	x	x		x	
R4b	Tutorials, Documentation & Support			x	x	x	x		x		x
R4c	Redistribution & Replication				x	x		x	x		x
R4d	Questionnaires	x	x	x	x	x	x	x	x	x	x

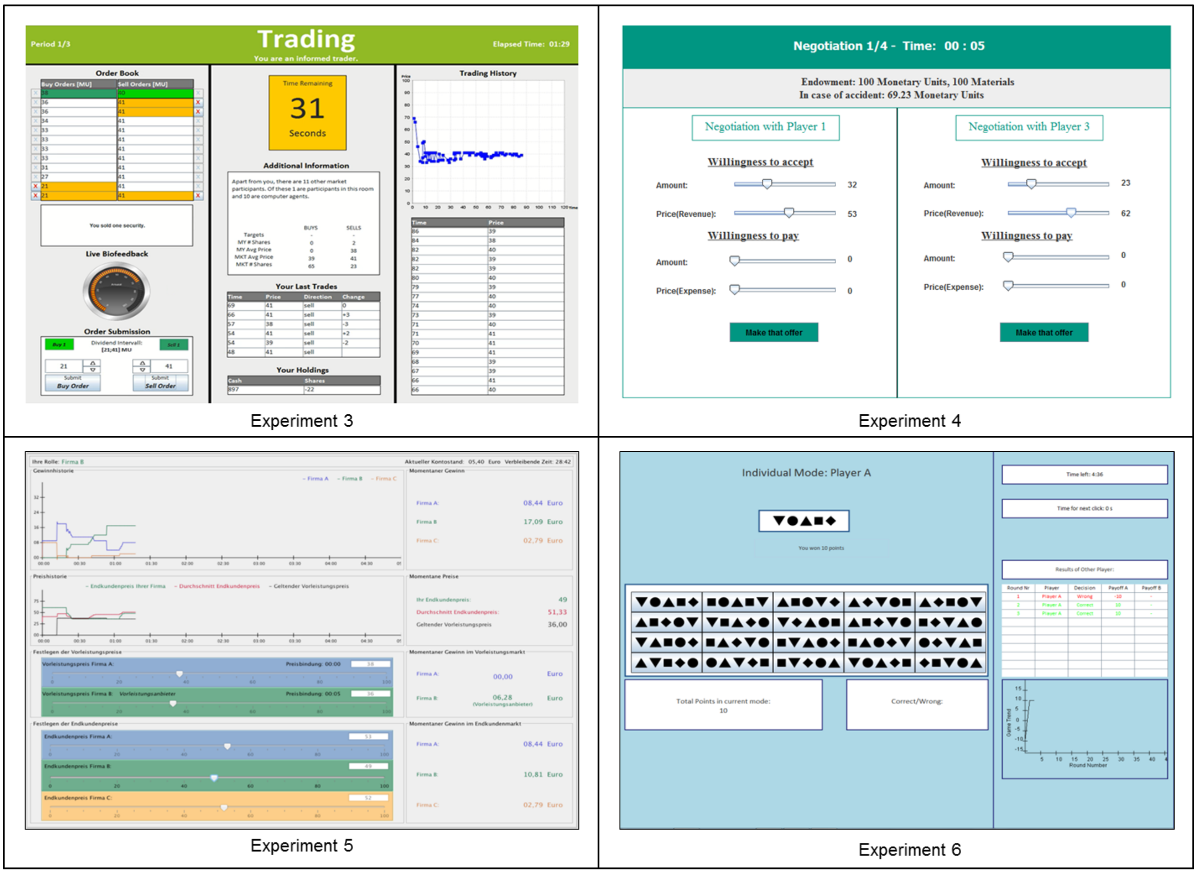

FIGURE 2.5: *Screenshots of experiments implemented on Brownie - I*

2.5.2 Evaluation of Requirements Based on a Literature Research

Next, we performed a thorough literature review of NeuroIS research in the Senior Scholars' Basket of Eight journals, which conducted an experiment with neurophysiological measurements to inquire upon their research questions. To ensure independent assessment, an evaluator who was not part of the developer team identified the requirements of the NeuroIS experiments conducted in these papers. The evaluator then validated whether Brownie meets these requirements or, if that was not the case, could be extended to do so. The results of the literature review are presented in Figure 2.7. Requirements marked as "fulfilled" are met by Brownie and have already been demonstrated as feasible in one or more experiments. Requirements marked as "requiring extension" are technically feasible, but have not been demonstrated by means of experiments yet. The literature review suggests that nearly all published NeuroIS experiments can be implemented in Brownie,

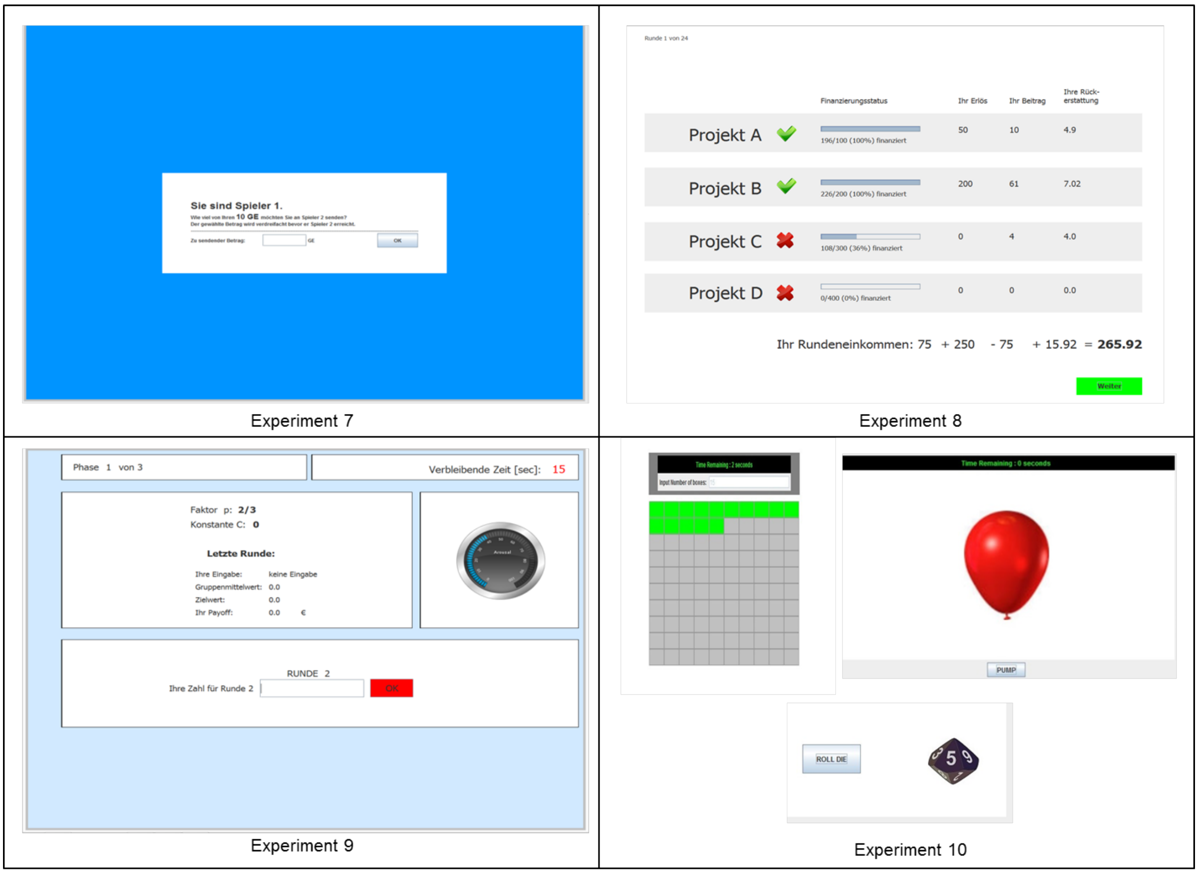

FIGURE 2.6: *Screenshots of experiments implemented on Brownie - II*

with the exceptions of Dimoka et al. (2010) and Riedl et al. (2010, 2014). These two experiments would require extending Brownie to integrate fMRI measurements.

During this evaluation step, we identified two requirements commonly mentioned in the surveyed NeuroIS papers, namely, integration of multimedia and questionnaires. Both requirements are implemented in the current version of Brownie, but were not explicitly noted as requirements in the original requirement list. Since the literature review showed them to be important across several NeuroIS papers, we extended the requirement list accordingly. This evaluation also highlights that the requirement list for the platform reflects the features required for conducting state of the art NeuroIS experiments, and will expand with the development of NeuroIS research.

FIGURE 2.7: *Mapping of NeuroIS experiments to requirements*

Mapping of NeuroIS experiments to requirements																				
Authors (year)	**Outlet**	**Description**	**Major Challenges**	**NeuroIS Method**	**Software used**	**N**	**R1a**	**R1b**	**R2a**	**R2b**	**R2c**	**R3a**	**R3b**	**R3c**	**R3d**	**R3e**	**R4a**	**R4b**	**R4c**	**R4d**
Astor et al. (2013)	JMIS	A biofeedback-based serious game for training emotion regulation skills.	Real-time biosignals to adapt the serious game to the user's physiological state.	HR	xAffect	104	●	○	●	●	●	●	●	●	●	●	●	●	●	●
Cyr et al. (2009)	MISQ	An experiment to examine responses to website images.	Design of treatments; Calibration & correction.	Eye-Tracking	Gaze-tracker	90	●	○	●	●	○	●	●	○	●	●	○	●	●	●
Dimoka (2010)	MISQ	An experiment to examine neural correlates of trust and distrust.	Stimuli manipulation; Correction of artifacts.	fMRI	SPM5	192	●	○	◉	◉	◉	●	●	●	●	○	●	●	●	●
Fadel et al. (2015)	JMIS	An experiment to study knowledge filtering process in online forums	To orient subjects to the Eye-Tracking instrument; reduce novelty effects.	Eye-Tracking	Tobii Studio	62	●	○	●	●	●	●	●	○	●	○	○	●	●	●
Gregor et al. (2014)	JMIS	A multi-method experiment of the nomological emotion network	Synchronizing EEG equipment data to subjects' website viewing activity.	EEG	EEGLab	62	●	○	●	●	○	●	●	●	●	●	●	●	●	●
Hu et al. (2015)	JMIS	An experiment to study decision-making in information security.	Paradigm design; Recording and correction of EEG, ERP computation	EEG	E-Prime	61	●	○	●	●	○	○	●	○	●	○	○	●	●	●
Kuan et al. (2014)	JMIS	An experiment to study opinions & emotions in group-buying	Group treatment manipulation, EEG data capture.	EEG	Emotiv Testbench/ EEGLab	18	○	●	●	●	●	●	●	●	●	●	○	●	●	●
Léger et al. (2014)	JAIS	The experiment to study neural reactions of users in a natural use context.	Reduce the artifacts; synchronize EEG and Eye-Tracking data.	EEG/ Eye-Tracking	Net Station/ Tobii Studio/ Noldus Observer	24	●	○	●	●	●	●	●	○	●	○	○	●	●	●
Li et al. (2014)	JMIS	A study on how game elements impact user engagement.	Record and interpret the EEG data from the gaming process.	EEG	Emotiv Testbench/ EEGLab	44	●	○	●	●	●	●	●	●	●	●	○	●	●	●
Minas et al. (2014)	JMIS	Responses of subjects to new information during a text-based ICT discussion.	Using multi-modal data to investigate subjects' cognitive and emotional responses.	EEG SC EMG	Emotiv Testbench/ MediaLab	44	○	●	●	●	●	●	●	○	●	●	○	●	●	●
Ortiz et al. (2013)	MISQ	A study to examine influence of events on IT use patterns.	Duration of experiment; Data from multiple modalities.	HR VPA;VR	Polar Software	161	●	○	●	○	○	○	●	○	○	○	○	○	●	●
Ortiz et al. (2014)	JMIS	A study to test the effect of factors for PU and PEOU.	Impedance and baseline; artifact correction.	EEG	B-Alert	24	●	○	●	●	●	○	●	○	○	●	○	○	●	●
Riedl et al. (2010b)	MISQ	A study on gender difference in online trust.	fMRI data collection; artifact correction.	fMRI	SPM5	20	●	○	◉	◉	◉	●	●	●	●	●	●	●	●	●
Riedl et al. (2014b)	JMIS	A trust game to investigate responses to human & avatar faces.	To accommodate subjects to fMRI; fMRI data collection and artifacts correction.	fMRI	Presentation/ FSL	18	○	●	◉	◉	◉	○	●	○	●	●	○	●	●	○
Tams et al. (2014)	JAIS	Multi-method validation between physiological and psychological measure of technostress	Acquiring pre-task measurements, noise control of sAA data, variables control	sAA	Salimetrics	64	●	○	○	○	○	○	○	○	●	●	○	○	●	●
Teubner et al. (2015)	JAIS	An experiment to study arousal and bidding behavior with humans/computer opponents.	Signal calibration; Artifacts avoidance	HR SC	z-Tree/ Ledalab	103	●	●	●	●	○	○	●	○	●	○	○	●	●	●
Vance et al. (2014)	JAIS	An experiment to examine EEG measures for risk perceptions.	Remove artifacts in the EEG data; examine the channels.	EEG	Geodesic EEG (EGI)	59	●	○	●	●	○	●	●	●	●	●	○	●	●	●

Note: N: number of observations; ○: Requirements not needed by experiment; ●: Requirements needed by experiment and demonstrated in earlier experiments by Brownie; ◉: Requirements needed by experiment, extensible in Brownie, with language wrappers. JAIS: Journal of the Association for Information Systems; JMIS: Journal of Management Information Systems; MISQ: MIS Quarterly; EEG: electroencephalography; EMG: facial electromyography; ERP: Event-Related brain Potentials; fMRI: functional Magnetic Resonance Imaging; HR: heart rate; sAA: Salivary Alpha-Amylase; SC: skin conductance; VPA: Verbal Protocol-Analysis; VR: Video Recording; FSL: fMRI Software Library; SPM: Statistical Parametric Mapping; z-Tree: Zurich Toolbox for Readymade Economic Experiments; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; ICT: Information & Communication Technology.

2.5.3 Evaluation of Requirements and Usability Based on a Case Study

2.5.3.1 Case Study Description

The goals of our case study were twofold: (i) whether Brownie meets the requirements of the experimenter and (ii) whether it achieves high usability for the experimenter as well as the participants of the experiment. The case study describes a research project that begun in March, 2015 which used Brownie and was broadly structured along the six essential phases of the NeuroIS research framework introduced by vom Brocke and Liang (2014). None of the developer team was involved in this project in any capacity. The project team contacted the developer team a few times asking for access to the software and inquiring about tutorials and support material for specific questions (see Case Study details). Two chief investigators (referred to as CI1 and CI2) planned to investigate user engagement on online participation platforms by comparing different crowdfunding mechanisms. CI1 had experience in programming with z-Tree, an alternative platform to Brownie (see Figure 1) while CI2 had minimal prior experience in programming (programming courses only, with no experience in programming projects). Both CIs had experience in experimental research. The CIs worked with two student research assistants (RA1 and RA2) on implementing their research project. Table 2 provides an overview of the data collected from the key persons involved in this project during one or more of the above mentioned six phases. We interviewed two participants of the experiment who were randomly drawn from the participant pool. In total, the research project lasted approximately 6 months, including all six research phases. The first two phases took up about 2 months, the implementation in Brownie (phase 3b) about 2.5 months, and conducting the experiment and analyzing the data took about 1.5 months.

2.5.3.2 Phases 1 & 2: Identify Research Questions and Build the Theoretical Foundation

In the first phase, the CIs identified the research questions for the project. First, they planned to investigate whether the crowdfunding mechanism would influence participants' behavior (RQ1). Second, they planned to examine whether interacting with a human or a computer group would influence participants' behavior and perceptions (RQ2). Third, they were interested in the influence of the crowdfunding mechanisms on the intensity of affective processes (RQ3). The CIs considered conducting an online study but discarded this option because "given the specific subject of crowdfunding" and the novelty of the approach, the CIs felt they needed the level of control provided by a lab experiment, with the appropriate choice of treatments. The experiment was to be supplemented by questionnaires to gather additional data required to investigate the above questions.

In this phase, requirements R1a, R1b, R3c, and R4d were already clearly perceptible to the CIs. CI2 explained that "We had to come up with a proprietary user interface, to simulate a crowdfunding setting, which was able to incorporate a number of projects. We wanted participants to see a progress bar (a graphical scale), and to be able to enter information. In addition, we needed to track each and every participant move (or click). We wanted a tool that enabled us to manage all participants to see the same screen and information during a given lab session, as well as a software that allowed us to track the timestamps of user activity. In addition, recording physiological data in the form of heart rate, was necessary, to assess emotional processes without direct reports of participants."

In summary, participants needed to interact with the interface (R1a), be grouped differently (R1b), their every click had to be logged (R3c), and a questionnaire had to be included (R4d). The CIs realized the need to gather physiological data in order to assess affective processes during participants' decision-making (R2a) towards the end of the conceptual phase. CI1 stated in the interview that one important issue was extending the round-based experiment to one in which participants could dynamically view others' actions, i.e. from a static experiment to one with a high level of real-time interaction. Hence, extensibility (R3d) was stated as an important criterion for platform choice as well.

2.5.3.3 Phase 3a: Design of the Experiment

The CIs decided on a between-subject design with different interfaces for two treatments (two crowdfunding mechanisms). With respect to group interaction (R1b), twelve participants were assigned to each session which in turn consisted of 24 periods. In each period, participants were randomly assigned to two groups of six, with the restriction that two participants would never be assigned to the same group twice. The design included three phases, or screens (Information and Input, Round Result, Final Result) with interaction elements, such as standard input boxes and buttons; and graphical elements, such as status bars, timer (ticking down from 60 seconds) and result tables. After each user input phase, an arrow or a cross would indicate which projects were funded. Hence, a common programming language which offered libraries for these elements, as well as supported their future planned extensions, emerged as an auxiliary requirement of the experiment (R3c) at this stage.

The CIs then turned to the question which platform would fulfill their requirements best. Limesurvey offered the required questionnaire functionality but neither biosignal acquisition nor processing nor sufficient flexibility in interface and experimental flow design. RA1 explained in their written feedback that, "[The] crowdfunding setting required a system that allowed us to specify detailed endowment rules and an advanced client-server communication." z-Tree was considered as another option but, as CI1 pointed out in the interview, "choosing [z-Tree] would not have enabled us to extend the experiment to a real-time setting [R3d]." CI2 stated in the interview that using z-Tree would have required them to drop R2 since it is currently not possible to acquire biosignal data in z-Tree. With regard to interface design (R3c), CI1 considered both z-Tree and other candidate platforms to be "limited in possibilities." CI1 and CI2 finally chose Brownie as their experimental platform since it fulfilled the primary requirements of the experiment (R1a, R1b, R2a, R2b, R3d, R4c, and R4d). CI1 and CI2 stated that system usefulness, i.e. that the system would meet all their requirements and be able to cope with their "special wishes," was initially the most important criterion in choosing Brownie.

2.5.3.4 Phase 3b: Implementation of the Experiment

In Phase 3b, RA1 and RA2 implemented the design specifications. The CIs provided power point slides for the screen designs, excel files for the group matching logic, screenshots of whiteboard discussions, mock-ups, and textual descriptions. RA1 and RA2 were also involved in the CIs' discussions. RA2 had basic programming skills, with prior experience in Java from university courses. RA1 had advanced programming skills, having participated in programming projects before. Both CIs estimated that, from their experience, it took them a normal amount of time (two weeks' time) to find a student research assistant reasonably fluent in Java, i.e. no longer than it would have taken to find a person with command of another programming language. CI1 observed that, in the beginning of the project, it was difficult to estimate the level of programming skills required for the project. Due to the complexity of the experiment, as well as the overhead of learning to work with a new platform, the CIs expected that they would run into difficulties implementing the experiment. CI1 explained that "it would have been easier to find someone to program for z-Tree, especially for simpler experiments, but not for programming our experiment -

which would have been a bigger challenge. z-Tree would have been useful for programming simpler settings, such as a standard public goods game, but for the crowdfunding setting we wanted to examine, along with physiological measures, Brownie turned out to be the better choice. In addition, on z-Tree, it is not possible to use common knowledge about programming, which makes one heavily dependent on the manual, whereas on Brownie, we could find help for new ideas on online materials, very easily."

Based on feedback from CI1 and CI2, RA1 altered the implementation iteratively. RA2 worked 10 hours per week on the implementation, and 80 hours in total, including the setup and learning time. The implementation phase consisted of the following four major steps (S1-S4).

S1 - Installation and Setup (03/11/2015 - 03/13/2015): RA1 and RA2 requested access to Brownie source code via email. The source code was distributed with links to tutorials, sample experiments, and video tutorials. RA1 found the information easy to understand and effective for installing Brownie, which points to a good information quality. CI1 remarked that "it would be helpful to have more of these great tutorials, but it is a good start ... " CI2 noted that it took more work than they had expected to install and setup Brownie, to understand the various components, and the interaction between them. However, as soon as a basic understanding was gained, they were able to make progress much more easily. CI1 recalls that RA1 was "frustrated in the beginning, but then with the video and online tutorials, they were able to set it up fast, and get it working," CI1 also noted that they would expect this to be a problem with any new experimental tool to be learnt.

S2 - UI and Client Screen Design (03/16/2015 - 04/15/2015): Based on the conceptual designs from Phase 3a, RA1 first designed the interfaces participants would interact with. This took approximately 40 hours. During this period, RA1 asked questions about how to quickly implement the GUI and the look-and-feel of client screens which the developer team answered by providing instructions for Window Builder and improving the tutorials on how to implement the GUI with Window Builder. With respect to the interface quality, RA1 stated in written feedback evaluation that, "After finding out how to do it, it is neat to be able to design an attractive experiment (using the WindowBuilder for eclipse) with Java."

S3 - Experiment Client-server Communication (04/23/2015-04/28/2015): RA1 proceeded with implementing the experimental flow, i.e. the ordering of displaying screens, sending client-specific information from the server, incorporating round-based, client-level, and group-level logic in the experiment. The developer team assisted in this step by pointing to current experiments as well as tutorials. RA1 stated as written feedback that "It was rather easy to include and start the experiment with its server/client interfaces."

CI2 found that "incorporating message passing client-server interaction was relatively easy," and CI1 did not "remember any problems in this step." The tutorials were considered particularly helpful for solving issues, which points to the fulfillment of R4b. CI2 commented on the information quality of the support material: "The information (such as videos, documentation) provided with Brownie as well as online support in forums was really helpful for finding the information required to complete the experiment." CI1 recommended for future work on Brownie that "the website's search and overview functionality could be improved such that tutorials can be found faster." CI1 emphasized the importance of R1a and R1b for their study design in written feedback: "The interaction of groups across different cohorts was really important to us. Specifically, group contributions and funding had to be calculated for each of the four projects and displayed to all participants. Brownie enabled us to achieve this."

In order to ensure that participants are not placed in the same group twice, the subject group allocation for each round had to be fixed in the implementation, whilst ensuring balanced treatments. The then existing features of Brownie (random vs. factorial) did not include this function. The developer and experimenter teams discussed this issue, and the developer team decided to extend Brownie to incorporate customized matching. It is now available for all experiments. This special requirement demonstrates R3d, i.e. the extensibility of the platform for a specific need. In their written feedback, RA1 commented on system usefulness: "It was nice to have pretty much all the freedom and possibilities anyone could ever ask for concerning the backend and which (matching) algorithms you want to include."

S4 - Testing (05/18/2015-06/11/2015): This step was completed in several iterations throughout the implementation process both in offline software testing and session testing in the lab. CI1 stated that it took some effort to start multiple clients (12, in this case) on the same system and test, but they managed to complete it successfully. CI2 stated that, initially, setting up each computer in the lab separately was a bit inconvenient. However, they later implemented a script based on a previous example for another experiment which solved this issue and made lab testing very easy. This demonstrates the advantage of using a common programming language (R3c), and the extensibility of the platform to incorporate desirable standard features easily (R3d). Testing took approximately a quarter of the overall development time of the research assistant (approximately 5 work days).

CI2 considered the tutorials, especially videos, to be "very helpful." CI2 would rate the difficulty of learning to use Brownie as "intermediate" (taking easy, intermediate, and hard as rating scale). CI1 found it more difficult to get a basic understanding of Brownie (see Installation and Setup) but thought that, thereafter, it was quite easy to understand how to adapt Brownie to different purposes and current and future research designs. In total, with respect to the overall satisfaction, all team members stated a satisfaction level of 4 on a scale of 1 to 5. They said that difficulties in implementation were partly due to the complexity of the experiment design, and partly due to insufficient documentation at the beginning of their research project. Since then, support materials and tutorials have been extended and elaborated: tutorials for all experiments are now publicly available.

2.5.3.5 Phase 4a: Conduct the Experiment and Collect Data

The study was conducted with twelve participants per session, and one session for each treatment (24 participants in total). CI1 stated that, with respect to interface quality, they were able to "...successfully and comfortably manage the flow of the experiment (such as configuring sessions, viewing session and client statuses during run-time), as well as programming additional elements (such as questionnaires), easily in the experiment using Brownie." CI2 added that the "front end was really good, and we needed minimal help in using it to manage the experiment. There were no issues during run-time of the session." CI1 stated that they incorporated pre-experiment questionnaires without any difficulty. Post-experiment questionnaires were collected via a separate Google forms website, which was invoked from within Brownie, as part of the website integration functionality (R3a). The advantage in invoking the Google form within Brownie was that - since the experiment was running in full-screen mode - participants were prevented from wrongly clicking on any other parts of the window, or closing the form accidentally.

In addition to behavioral data, the experimenters also collected ECG and EDA data using the Bioplux (2007) sensor system, which was transmitted using Bluetooth and stored on the individual participant's PC, thus demonstrating fulfillment of R2a. CI2 stated that "Brownie gave us the opportunity to log any user event in the experiment and synchronize them with the physiological data with the required timestamp information," thus demonstrating R2b. They were able to complete the experiment successfully, and integrate data for their analysis. This demonstrates fulfillment of R3a (integration of websites) and R4d (implementation of questionnaires). CI1 emphasized that the flexibility aspect (to incorporate new ideas) was the most satisfying aspect of programming with Brownie, and they felt "limitless" in terms of what they would be able to implement in their project. RA1 summarized in the written feedback, "All in all, Brownie worked as we wanted it to." CI1 added that Brownie matched their expectations with respect to system usefulness and overall satisfaction.

In order to gauge the participants' views in using the interfaces implemented in Brownie, we interviewed two experiment participants (EP1 and EP2) to obtain qualitative feedback on the usability of the platform. EP1 had already taken part in experiments on z-Tree and Brownie before that had been set in similar group interaction scenarios. EP1 stated that the experiment interface was self-explanatory and easy to interact with, due to its clear structure. They felt absorbed in the experiment but would have liked to avoid "uninteresting" waiting times while other participants were finishing their respective tasks. These waiting times were due to the CIs' decision to go with a round-based design; they indicated in the interview that they plan on changing to a dynamic design in a follow-up experiment. EP1 did not discern any visible differences between using interfaces programmed with Brownie or other platforms. The participant suggested that incorporating a chat function would have enabled communication with other participants. Although a client-to-client communication feature is available in Brownie, the CIs had decided against enabling it in order to maintain a higher level of experimental control. Comparing two experimental interfaces implemented on Brownie (both of which the participant had taken part in), EP1 rated the satisfaction level of the crowdfunding experiment as 4, on a scale of 1 to 5 and the interface of the other experiment as 5. That interface had contained real-time elements (such as live charts and trends, also implemented in Brownie), which appealed more to the participant. EP1 had taken part in another experiment with physiological measurements before, and found the overall experimental interface to be engaging.

EP2 had not taken part in an experiment with Brownie before, but in several experiments with z-Tree. They found participating in the crowdfunding experiment interesting, and thought it felt real to an extent. EP2 felt that this was one of the "better" experiments they had participated in so far, that the interface was absorbing and fun, and that they were not bored during the experiment. Comparing Brownie with z-Tree, EP2 stated that the structure of the crowdfunding experiment was comparable (information, decision, and result). They observed that - compared to previous experiments on z-Tree - loading time of experiment screens, especially those with a lot of information, was much shorter. In the previous experiments, they had found the long loading times of such screens rather tedious. On a scale of 1 to 5, EP2 rated the satisfaction level of the crowdfunding experiment as 5. In summary, the above statements point to a satisfactory and engaging interface quality of the participant screens.

2.5.3.6 Phase 4b: Analyze Data

With respect to flexibility of user data logging (R3b) and system usefulness, RA1 stated in written feedback that, "[Brownie was] used for data storage, and data storage methods used in previous experiments were useful examples to easily integrate these in our experiment," and also that "the pre-defined database helped a lot," referring to the underlying database schema of Brownie designed for easy querying and re-organizing of experimental data. In particular, client data was stored by concatenating relevant user values (e.g. input and click data) along with the respective client timestamps in the central server database. To retrieve more information on different granularities like subjects, round, group-level join queries were used. This increased system usefulness in terms of flexibility of data storage. CI1 said that "... (working with) normal (i.e. observed data about participant behavior) data was no problem. Brownie further enabled the synchronization of physiological data, with the events of the experiment, by adding timestamp entries. These time-synced event entries were later useful for analysis of physiological data. However, physiological data extraction can be improved." CI1 specifically suggested reducing the steps necessary for transformation and analysis of the stored raw physiological values.

2.5.3.7 Phases 5 & 6: Interpret the Experimental Data and Discuss the Results

The CIs proceeded to analyze the experimental data, and publish their findings in suitable outlets. In future sessions, they plan to store real-time processed physiological data in addition to the raw data. CI1 observed that, "in all our decisions, we never came to a point where we could not do something because it was not possible on the platform. There was always a solution, and this was a very positive aspect for us." CI2 gave as their opinion that, "[Brownie] is an excellent alternative to z-Tree. The possibility to include physiological measurements is really important, since they help understand participant behavior greatly." CI1 considered physiological data to be "honest" - in terms of showing whether participants were aroused, annoyed, or bored during an experiment. Both CIs were of the opinion that integration of physiological measures would be extremely useful for upcoming studies in the IS domain. If CI2 were to do another experiment, they would "implement it with Brownie." CI1 and CI2 stated that they did not notice a marked difference to other platforms while conducting their experiment, since the core building blocks (such as session, treatment, and periods) were similar to other platforms they used before. In future research, they plan to extend their experiment by new treatment levels. This demonstrates fulfillment of R4c, i.e. the replicability of an experiment using Brownie, and also demonstrates the overall satisfaction with Brownie, emphasized by CI1's statement that "I would be comfortable to design and create my next planned experiments in Brownie, and I would recommend it to other researchers." The CIs also stated, with the benefit of hindsight, that the quality of the available information played a large role in helping them to successfully complete their project.

2.5.4 Evaluation of Usability Based on an Experimental Study

2.5.4.1 Experimental Study Description

We evaluated the usability of Brownie for experimenters by conducting a laboratory study to compare Brownie to the current gold-standard in software for behavioral experiments, z-Tree. The study task consisted in altering a provided Ultimatum Game to a Trust Game. Specifically, participants had to change the experimental logic (1) and the interface (2), add player pictures (3), a reputation score (4), and include biosensor measurements (5). The Ultimatum Game is a two-person game in which the first player (the requester) receives a sum of money and proposes how to divide the sum between himself and another player. In the Trust Game, the differences are that the responder will be given a choice how much of the now-tripled money to send back to the requester. We chose this setting because, since the Ultimatum Game (Joe and Lin, 2008) and the Trust Game have been used for understanding peer-to-peer interaction and trusting behavior in online environments (Riedl et al., 2014; Dimoka et al., 2011; Gefen and Pavlou, 2012).

2.5.4.2 Procedure

The study was carried out in a within-subject design, where a participant would implement the experiment in both Brownie and z-Tree. The two treatment sessions (Brownie and z-Tree) took place in two subsequent weeks, at the same time of day and the same laboratory. Participants were randomly assigned to one of the treatments in the first week, and alternated to the other treatment in the second week.

The study proceeded as follows. First, participants were given general instructions on the study task. Second, they filled in a pre-study questionnaire on their programming abilities. Third, they received a tutorial explaining the Ultimatum and Trust Game rules, how the Ultimatum Game was implemented in the software, and which changes were necessary to alter it into a Trust Game. In order to ensure that the depth of the instructions, and the information on the tutorials for both platforms were comparable, the same tutorial was adapted for the other platform, and modifications were made only with respect to the platform-specific terms, while retaining the task descriptions and modifications. The study task was divided into eight subtasks. After each subtask, participants were given a short questionnaire on how difficult they felt the task had been. After the last task, participants were given a final questionnaire asking for their overall usability evaluation of the software. We measured usability with the IBM usability scale (Lewis, 1995). Participants were on a time limit of 120 minutes. Prior to the study, we estimated the time required for each subtask by way of timing 6 student assistants with no or limited prior experience with Brownie and z-Tree and averaging their results.

2.5.4.3 Measures

Task scores were assigned based on successful lines of code which were functionally correct for performing the given task. Each task was hence broken down into 3 or 4 code alterations, which were specified for both platforms. The degree of task completion was scored by two independent researchers based on the solution code submitted by participants. For measuring usability, three factors from the IBM usability scale were used, namely System Usefulness, Information Quality, and Interface Quality. Confirmatory factor analysis with R-3.3.2 and lavaan 0.5-20 showed good model fit.

2.5.4.4 Sample

We invited students from a course on experimental methods in business research, in order to ensure that all participants had a basic understanding of and a general interest in experiments and experimental research, of which 28 students participated. For participation in the usability study, students were awarded by means of course credit points. The study was carried out in the experimental lab at [blinded for review]. Prior to our study, the Ultimatum Game had been briefly explained within the scope of the course, the Trust Game had not. Experimental platforms had not been discussed in the course up to this point. 25%

of participants were female, and students were pursuing their Master's degree. Average session duration was 1:33 hours in Brownie, and 1:26 hours in z-Tree.

2.5.4.5 Results

Figure 2.8 shows the average task scores of our participants on z-Tree and Brownie, indicating how well they solved each task. Task 8, the configuration of biosensors, was unique to Brownie. Our results indicate that, on average, participants performed better on Brownie, with the exception of tasks 4 (adding Responder logic to interface) and 7 (accessing experimental data). Taking the results by session, participants performed better in both platforms in the second session (completion rates increased from the first session by 19% in Brownie, and 10% in z-Tree), which can be explained by learning effects about the study task.

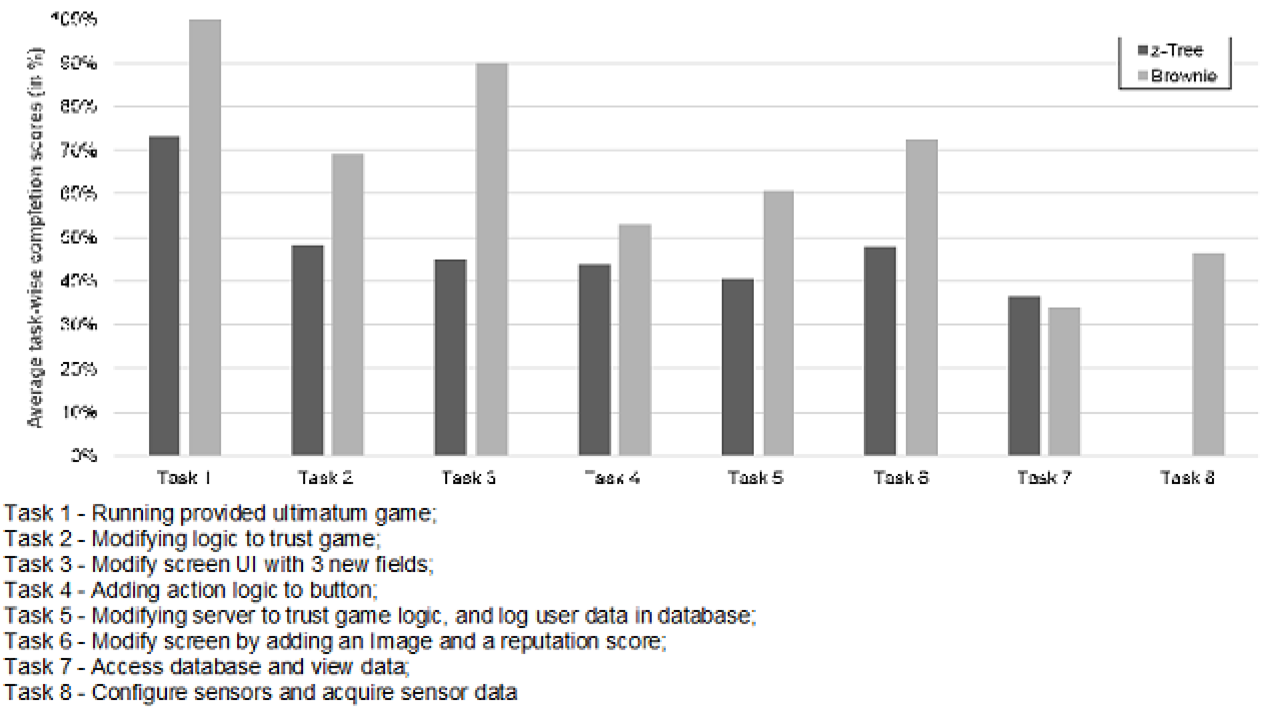

FIGURE 2.8: *Task completion rates for Brownie and z-Tree*

Our results show that Brownie compares well to z-Tree; participants rated it as good as z-Tree in both overall usability and all three usability sub-scales (Figure 2.9). Mean and median ratings of all scales were lower for both platforms in the second session, but not significantly so.

Y-axis indicates usability ratings aggregated across subjects, platforms, and on two different days, on a scale of 1-7. Smaller box plots indicate higher agreement within subjects, which is observed in the case of z-Tree in Day 1, and Brownie for Day 2. Differences between the groups were not visible, denoting comparable usability. Long lower (upper) whiskers indicate that participants varied more over the lower (upper) quartile of the usability score.

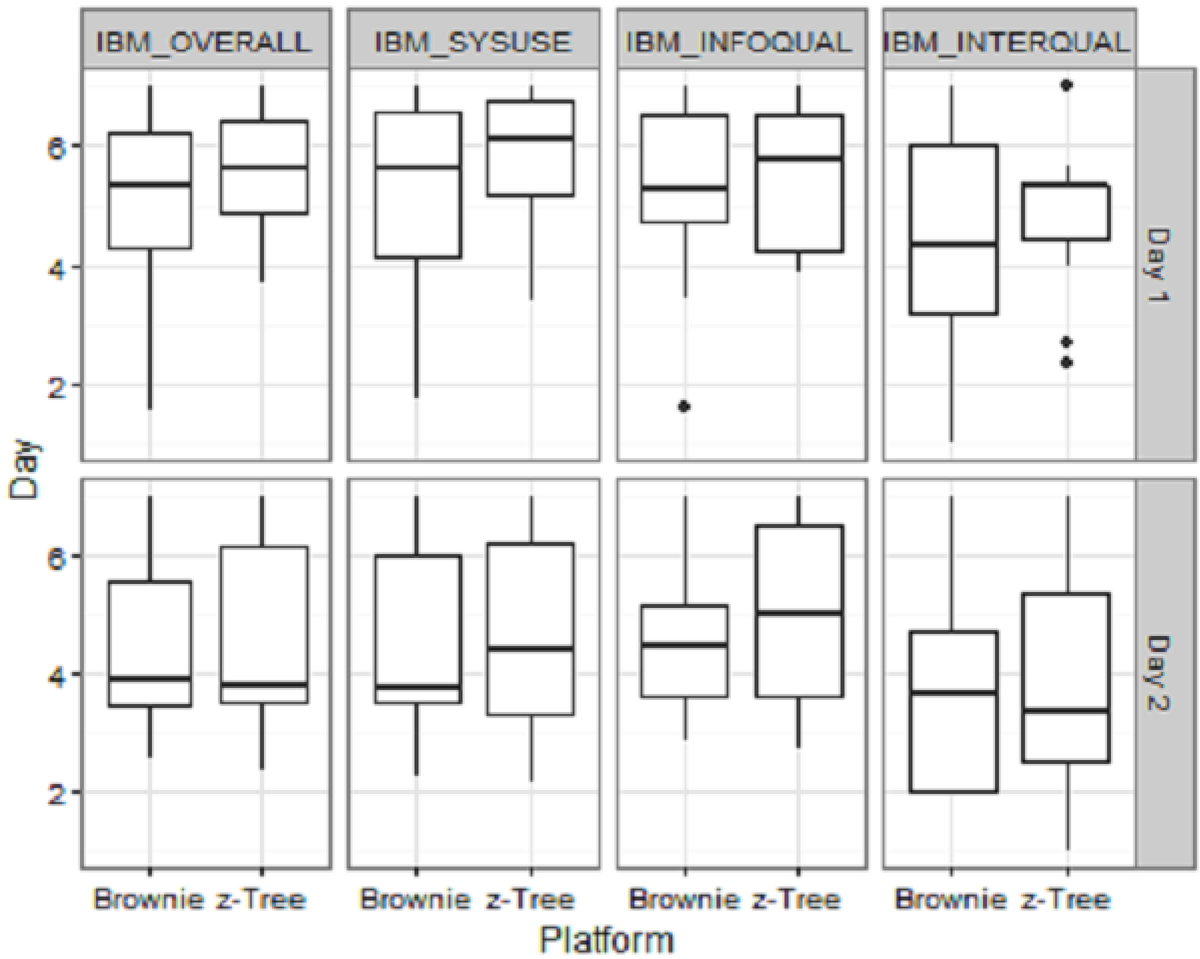

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FIGURE 2.9: *Usability scores for Brownie and z-Tree*

In an open feedback question at the end of the second sessions, participants were asked to indicate whether they would prefer to use Brownie or z-Tree in the future. 12 participants indicated a preference for Brownie, citing reasons such as flexibility, common programming language, open-source, and more intuitive programming. 8 participants preferred z-Tree because they found it easier to understand. 6 participants did not express a preference, and 2 participants explicitly noted that they were unable to decide, stating that they found Brownie more flexible and powerful but z-Tree easier to get started with.

Taken as a whole, the results of the experiment show that, in terms of usability Brownie is comparable to the current used software z-Tree, while considering common aspects of experiments (such as experiment logic and UI modification). At the same time, Brownie offers additional NeuroIS-specific features which are currently not available in z-Tree (R2a, R2b, R2c), as well as possibilities for further extension (R3a, R3c, R3d, R4a). The requirement list identified earlier in the chapter has been confirmed by the literature review, as well as the case study. Hence, we conclude that, Brownie meets emerging requirements of NeuroIS research and cognate areas, which are not fulfilled by current platforms, and is usable to implement NeuroIS and cognate experiments.

2.6 Contribution and Discussion

In Chapter 2, we describe Brownie, a stable platform for implementing user interaction experiments with neurophysiological measurements and strategic interaction scenarios. In terms of dissemination and communication, the source code for the platform is distributed as a ready-to-use eclipse workspace project, with version controlling enforced through the use of Github. The source code is available along with a Wiki with a setup tutorial, a quick start guide, and a step-by-step guide to program and manage an experiment. In addition, video demonstrations on "How to setup Brownie", and "How to Setup an Experiment", are made available at the following URL (https://bitbucket.org/kit-iism/experimenttool/wiki/Home). The URL also contains the API, which describes the interrelationship between the various projects and classes in Brownie. Finally, the research purpose behind the platform is communicated by means of scientific articles.

Addressing the design objective stated at the beginning of the chapter, we herewith identify requirements to be fulfilled by a potential platform for conducting NeuroIS research in the lab. The platform is hence developed iteratively, by first identifying preliminary requirements, and then using evaluations to develop and identify further requirements. At the current stage of the project, there exists a small active community of users of Brownie, that develops experiments, improves the framework, and provides necessary tutorials and support required for new users. While the platform core is expected to be stable, it is possible to modify and extend the framework as per the requirements of the individual researcher.

2.7 Limitations and Future Work

This research has several limitations. First, in its current form Brownie does not allow direct integration of available neuroimaging techniques (such as fMRIs, or PET). Such imaging techniques predominantly use Python, Matlab, or C++ for data acquisition and Matlab for further analyses. One possible solution would be providing suitable wrappers to the other languages in order to facilitate communication with a broader range of sensors, which is possible in Java. The existing implementations of live-biofeedback are based on heart rate and skin conductance sensors, and ought to be enhanced in terms of efficiency and real-time aspects of live-biofeedback, and in terms of other sensors that can be used to compute LBF, such as PPG, EMG, etc.

Second, design science problem is conceptualized by means of the proposed requirement set. Although we attempt to present a design artefact, evaluate it, and provide directions for further development, the requirement set may also be validated by means of other design instantiations (Gregor and Hevner, 2013). These instantiations could adopt a different design artefact for each requirement, such as choosing a different language for the implementation. Other design instantiations may arise as a result of further experiments conducted with Brownie, or by replicating existing experiments in different geographical or cultural contexts.

Third, the real-time signal processing capabilities in Brownie are based on heart rate and skin conductance sensors. The processors used to compute the respective features ought to be enhanced in terms of efficiency and real-time aspects, and in terms of extensibility to other sensors, such as PPG, EMG, and EEG (Pope et al., 1995). The modular architecture of Brownie facilitates extensions of the real-time features, such as different manifestation of live-biofeedback, altering and adapting the interface based on neuro-information, etc. In addition, integration with statistical and data analysis modules, such as R-packages, would make it possible to perform the analysis of experimental data within the platform environment, if required. These analysis modules could enable building individual variances in real-time sensor-data processing, based on gender, age, or historical data of participants.

Finally, with the proliferation of mobile devices and the variety of tasks being performed on them, NeuroIS experiments would need to be conducted across different devices, to understand user engagement with mobile devices (Bhandari et al., 2015; Hollingsworth and Randolph, 2015). Brownie currently does not support experiments with mobile applications, and in the future, it could be extended to incorporate experiments applying NeuroIS methods with mobile applications and sensors.

2.8 Conclusion

Brownie serves as a solution that meets emerging requirements for conducting NeuroIS research. At present, the effort and technical knowledge required to conduct NeuroIS research are substantial. With this platform, we aim to help reduce both to a better manageable level. We also attempt to provide a high degree of flexibility with regards to individual experimenters' needs, specifically extensibility to emerging NeuroIS methodologies and scalability across various devices. We hope that Brownie contributes to future research in individual and group interactions in the lab by leveraging existing and emerging NeuroIS methods for user interaction research, and fosters research collaboration across cognate domains.

In the following chapters, we will now raise and examine specific NeuroIS research questions, which also serve as instantations of how Brownie may be used for behavioral research. The first study was implemented on z-tree (Chapter 3), and the second and third studies were implemented on Brownie (Chapters 4 and 5).

Chapter 3

Emotion regulation and behavior in trading: to sell or to keep

> "We cannot tell what may happen *to* us in the strange medley of life. But we can decide what happens *in* us, how we can take it, what we do with it, and that is what really counts in the end.
>
> JOSEPH FORT NEWTON (1876-1950)

3.1 Introduction

External events and stimuli are circumstances that shape our behavior and decisions (Bechara and Damasio, 2005). As stated in the epigraph, we often may not be able to regulate or decide the occurrence of external events, which decide our course of action. However, such events, more often than not, cause changes in our emotional state, thus impacting subsequent behavior, positively or negatively. The extent to which these emotional changes impact our subsequent behavior, depends to a large extent on the way we regulate emotions, and the degree to which we are able to regulate their impact, consciously or subconsciously. This ability to influence how we can take what happens to us, may be formally termed as emotion regulation. Theoretically, there exists several emotion regulation strategies. In this chapter, we focus on two such strategies, namely suppression and reappraisal, and study the impact of external events, namely gains and losses, on emotions and trading decisions.

Recent literature in decision-making and behavioral economics reveals that a large segment of investors, when dealing with situations of probabilities and higher valuations, does not maximize their expected outcomes in decisions (Kahneman, 2003). The expected-utility theory (EUT) serves as a benchmark model for decision-making under risk (Bernoulli, 1954). Briefly summarizing, the model assumes that people choose between alternative courses of action by assessing the desirability or utility of each action's possible outcomes and linearly weighing those utilities by their probability of occurring. Having said this, several theories dealing with generalizations of EUT are however context dependent, and struggle to provide a satisfactory explanation for the observed behavior, as predicted by Huck and Weizsäcker (1999). Many of these theories do not take into account that investors' behavior often deviates from decisions that maximize the expected value of a decision, possibly due to difficulties in determining the probability of occurring (hence the risk) and expected monetary profit of each decision in the "real world."

In this context, the influencing role of emotional arousal and their regulation has been recognized in recent research on decision-making, to explain and account for these deviations. Rick and Loewenstein (2007) coined the term integral emotions, which arise from thinking about the consequences of one's decision, and which are experienced at the moment of choice. For instance, while deciding whether to buy or sell a stock, a person might experience immediate fear at the thought of the stock's losing value, and hence opt for a different strategy than the one that maximizes his/her expected value. While the role of integral emotions has been identified, several individual differences exist in these theories as well. To this end, differences in the way people regulate emotions has started to emerge as an explanation. For instance, Heilman et al. (2010) report that the effects of integral emotion on decisions vary according to the manner in which a person regulates the emotion experience, and this determines his/her performance in a given task. People who cognitively change a situation's meaning in a way that alters its affective impact (reappraisers) were found to display increased risk taking, by reappraising negative emotions associated with risk. Another strategy is by modulating responses after they occur by influencing physiological, experiential, or behavioral responses as directly as possible. Suppression falls under this category, and people who are predominantly suppressors, for instance, were shown to exhibit the same level of risk aversion, since suppression was ineffective in regulating negative emotions. Hence, it appears that the emotion regulation (ER) strategy employed by a person is likely to determine how affect is experienced as well as processed, to arrive at a decision. It is this intriguing interrelationship that we attempt to examine in this chapter.

RQ1: In an individual context, do emotion-regulation strategies moderate the role of integral arousal on EV-maximizing behavior, particularly in dealing with the external influences of gains and losses?

Explicitly stated, in a trading context, we ascertain whether ER influences the level of integral arousal, measured by physiological responses. If so, does ER moderate the impact of integral arousal on EV-maximizing behavior? The first set of hypotheses hence tests whether reappraisal/suppression strategies correspond to differences in experienced arousal level, and moderate arousal to increase/decrease EV-maximizing behavior. Second,we test the same set of hypotheses, but under the premise that a gain/loss has been experienced (correspondingly, a positive or a negative affect). In order to do this, we conducted a laboratory experiment in which subjects participated in a complete information path-independent repeated stock-trading game. After observing the stock's first price change the subject decides whether to hold or sell the stock, and then receives one trend update after this decision. During the experiment, subjects' emotional arousal, which occur in the course of the decision process, is recorded by physiological parameters such as skin conductance response (SCR) and heart rate (HR) which are well-established proxies for affective processing (Dawson et al., 2011). Questionnaires were employed to measure ER strategies (Gross, 2007) and risk attitudes (Holt and Laury, 2002).

The results show that subjects applying cognitive reappraisal experience lower levels of integral arousal (measured by HR and SCR), whereas suppressors experienced higher levels of SCR. Secondly, reappraisers were significantly less affected by emotional arousal, to exhibit more EV-maximizing behavior. A similar effect has however not been observable for subjects who applied suppression strategy. Thirdly, after experiencing losses (and gains), reappraisers experienced lesser levels of arousal (SCR and HR), whereas suppressors exhibited an increased level of arousal (SCR) after gains and losses. Finally, applying the strategy of reappraisal, particularly after experiencing a loss, related to an increased number of EV-maximizing choices. This effect was not visible in the case of experiencing gains. Also, applying a suppression strategy did not moderate the impact of arousal on EV-maximizing behavior, for gains or losses. The findings of this chapter implicate that reappraisers not only experience lower levels of arousal, but adopting a reappraisal strategy has a positive impact in maximizing expected value of a decision, and additionally so, after experiencing a loss. Therefore, cognitively altering the impact of a consequentialist decision appears to be effective in decision-making, whereas strategies that hide or ignore the emotion may not be equally effective.

The remainder of this chapter is structured as follows: We first summarize existing research on the influence of emotional arousal and individual ER strategies on decision-making and trading. From these foundations we derive the hypotheses, followed by the experimental design of the study. The results of the experiment are then presented, followed by conclusion and discussion of the findings.

3.2 Theoretical Background

In order to study deviations from EV-maximizing behavior, both information on probability of winning and valuations, albeit fundamental are essential to incorporate. We begin with two properties of a stock, in defining what would be expected behavior under the EUT. We then seek to understand how and why subjects' ER strategies play a role in their emotional arousal levels, and when they deviate from expected behavior. In the following, we lay down the theoretical background with respect to emotional arousal and emotion regulation strategies, and their influences in decision-making.

3.2.1 Emotional Arousal in Decision-making

Many models in decision theory assume that agents, or decision-makers maximize their expected utility taking the impact of context-specific factors into consideration, such as probability of occurrence, and valuation. They evaluate all possible states and actions independent of whether these states will be reached or not and solve the game by backward induction (Fudenberg, 2006). This means that the behavior of an agent or a user is assumed to be not affected by events that might occur, such as gains or losses. Rather, all possible contingencies are dealt with by a complete plan of action that is made up prior to the start of the decision-making context (such as an auction) and remains unaffected by its actual course (Adam et al., 2011).

Usually, an emotion is triggered in response to an emotionally competent stimulus (Bechara and Damasio, 2005), i.e. a particular object or event associated with a subjective significance, such as experienced gains or losses. Taking these into account, defining

EUT might hence not be the complete picture in trying to understand economic behavior, since it does not take these gains and losses into account, and neither the emotions elicited by these events. The role of emotions in economic behavior (as prescribed by EUT) has recently become a subject of wide debate (Bechara and Damasio, 2005; Humphrey, 2004). Rick and Loewenstein (2007) presented innovations to the EUT by involving the influence of expected and immediate emotions in risky decision-making. To elucidate further, expected emotions are those that are anticipated to occur as a result of the outcomes associated with different possible courses of action. The key feature of expected emotions is that they are experienced when the outcome of a decision materializes, but not at the moment of choice. Immediate emotions, in contrast, are experienced at the moment of choice, falling into one of two categories: integral and incidental. Integral emotions arise from thinking about the consequences of one's decision. Incidental emotions arise from sources objectively unrelated to the task at hand (e.g., being disturbed due to loud music played elsewhere). Of these, it is likely that integral arousal impacts the course of behavior in a decision-making context, since it is both related to, and occurs prior to the decision. Hence, as a proxy for integral arousal, physiological measurements were performed at events where integral arousal is likely to be triggered.

Numerous research works draw upon integral arousal (using physiological measurement) in order to study economic decision-making. For instance, SCRs were measured in subjects involved in a gambling task (Bechara, 1997), and the results indicate that anticipation of the more risky outcomes led to higher SCRs than of the less risky ones. When gambles that involve possible gains are presented one at a time most people display an appeal towards the gambles. This phenomenon of gaining satisfaction directly from the riskiness of the situation has been termed as the attraction to chance, and of suffering dissatisfaction directly from the riskiness of the situation, repulsion from chance (Albers et al., 2000). Adam and Kroll (2012) established through experiments with physiological measurements that attraction to chance can be indicated by differences in arousal based on the choices made by people for different types of lotteries. Adam et al. (2011) showed that arousal as measured through HR mediates the influence of time pressure on bids in Dutch auctions, also validated in the case of computerized agents in Teubner et al. (2015). Yet another instance is of Astor et al. (2013) who showed in first-price sealed bid auctions that higher valuations yield stronger responses in HR and SCR than lower valuations. Since emotions have shown to be correlated to both the fundamental factors (of risk and valuations), and can be measured by means of SCR & HR, physiological measurements at specific events before the decision are employed to test the hypotheses in this study.

3.2.2 Emotion Regulation

An emotion implies action tendency, i.e., the urge to execute a particular action (Frijda, 1988). However, whether or not an action tendency results in action, depends heavily on the regulation phase, wherein the consequences of executing an action tendency are evaluated (Frijda, 1987). This regulation phase depends both on an individual's ER capabilities and on the intensity of emotion. If the intensity of emotion is very strong, the individual may surpass "regulation thresholds" or "points of no return" (Frijda, 1987) and hence have lesser control over the influence of emotional arousal on his/her actions (Loewenstein, 1996). On the other hand, if the individual were conscious of experiencing an emotion, the chances are higher that he/she is able to control the influence of emotional arousal on behavior, inspite of the intensity. Hence, theoretically, the very experience of emotion seems to be heavily influenced by this regulatory mechanism, and dictates to what intensity (arousal), and in which direction (valence), an emotion is expressed.

Given their more ancient role in decision-making, Panksepp (1998, 2005)'s framework posits that the affective aspects of a stimulus are processed before and independently of any cognitive aspects. Berridge and Winkielman (2003) report evidence for the idea of unconscious emotion alone (for instance, unconscious liking), without any cognitive influences. In this work, we adopt the theoretical framework of reference as suggested by Walla and Panksepp (2013): although unconscious processing also occurs when related to emotion, it needs to be distinguished from the concept of emotion, which denotes the output of information processing. What's unconscious here should be rather termed as "affective information processing"[1]. Raw affective information is able to elicit more than just one emotion, which can even be differently valenced. However, affective processing also occurs in the absence of emotion generation. Finally, emotions are principally independent from cognition. Cognition, is regarded as a separate, parallel function, which can synergize with as well as interfere with affective information processing.

It has been shown that regulating emotional arousal is dependent on the innate qualities and regulation strategies that a person (consciously or unconsciously) employs. Gross and John (2003) illustrates methods that can be employed to identify these individual characteristics. Here, two types are distinguished: reappraisal and suppression. Reappraisal occurs and intervenes before emotion response tendencies have been fully generated, referred to as an antecedent focused strategy (Gross, 1998). It pertains to cognitively chang-

[1]Note that this is slightly different to Bechara and Damasio (2005), whose definition states that an emotion is triggered in response to an emotionally competent stimulus

ing a situation's meaning in a way that alters its affective impact. Employing reappraisal strategy has thus shown to efficiently alter the entire subsequent emotion trajectory, especially when down-regulating negative emotion. For instance, thinking about the positive side of a negative incident or putting it into the broader context, might alter the intensity as well as the experience of a negative affect. Reappraisal might hence be an adaptive strategy that reduces negative affect, and in some contexts also decreasing the level of physiological arousal (Delgado et al., 2008; Sokol-Hessner et al., 2009).

In contrast, suppression comes relatively late in the emotion-generative process, and modifies the behavioral aspect of emotion response tendencies, referred to as a response focused strategy (Gross, 1998). Suppression refers to influencing physiological, experiential, or behavioral responding as directly as possible. Suppression could also refer to efforts to hide what one is feeling, or attempts to inhibit what one is feeling. Use of suppression was shown to be correlated with increased negative affect, poorer recovery from changes in negative affect, and decreased self-efficacy for managing future emotions (Gross, 2002).

How are these regulating strategies relevant to the role of emotions in economic behavior? Recent evidence illustrates that effective ER can reduce loss aversion and therefore be beneficial for decision-making (Sokol-Hessner et al., 2009). Barrett (2007) showed that due to their enhanced ability to differentiate emotions and to control their biases, investors were able to achieve better decision-making performance. Thus, whether emotions enhance or deteriorate decision-making performance is likely to be moderated by whether people are able to identify emotions as a first step, and then whether they are able to regulate them, and if so by which method.

Moving to another specific example, Heilman et al. (2010) elucidates that upon inducing the emotions of fear and disgust, reappraisers reported reduced negative affect and this was associated with reduced risk taking and increased task performance (by achieving higher scores in the Balloon Analogue Risk Task, BART). This suggests that reappraisal aids to decrease the role of negative affect and improves performance in a given task, in comparison to suppressors, where the latter was not observed. By means of Blood-Oxygen-Level-Dependent (BOLD) contrast imaging, Martin and Delgado (2011) also illustrate that cognitive control over affective response can modulate neural responses, and promote more goal-directed decision-making (reduced risk taking). Fenton-O'Creevy et al.'s (2011) qualitative study summarizes opinions and interviews with traders, that successful and profitable trading was in fact associated with more sophisticated techniques for regulating one's own affective state. Hence, it appears that ER plays a vital role in determining whether a person's emotional arousal impacts his/her behavior. However, is has not yet been investigated, whether (i) ER strategies increase or decrease the influence of (measured) emotional arousal, in the context of EV-maximizing behavior, and (ii) to what extent the influence of emotional arousal on behavior is in turn moderated by ER strategies. We hence investigate whether applying an ER strategy (of reappraisal/suppression) moderates the role of emotional arousal, and leads to (enhanced/decreased) EV-maximizing behavior. To this end, the first two hypotheses can be stated as follows:

Hypothesis 1.1: Applying reappraisal strategies (a) corresponds to lower experienced arousal level and (b) moderates the role of integral arousal on EV-maximizing behavior, leading to more EV-maximizing behavior.

Hypothesis 1.2: Applying suppression strategies (a) corresponds to lower experienced arousal level and (b) moderates the role of integral arousal on EV-maximizing behavior, leading to less EV-maximizing behavior.

We next turn to the distinction between positive and negative emotions, and the role they are likely to play in determining EV-maximizing behavior. Previous studies have shown that happiness reduces risk aversion, whereas negative emotions such as fear increases risk aversion. Specifically, Lerner and Keltner (2001) reported that while fearful people expressed pessimistic risk estimates and risk-averse choices, angry people expressed optimistic risk estimates and risk-seeking choices. Loewenstein (2000) documented that during risky decision-making, negative feelings (i.e., fear, dread, or anxiety) towards risk tend to dominate positive feelings. Hence, it is possible that negative feelings are dealt with differently, especially when the factor of risk is involved, thus suggesting the role of ER strategies. Indeed, measuring the extent to which participants experienced positive and negative emotions, Gross and John (2003) show that reappraisers experience and express greater positive and less negative affect, whereas suppressors experience and express less positive emotion. Heilman et al. (2010) takes these concepts together and, by means of self-reported emotions and the BART, establishes that participants who reappraised their negative affect displayed increased risk taking and increased task performance. However, the direction in which ER strategies moderate the influence of emotion, specifically distinguishing between positive and negative emotions, on behavior is not certain. To the best of our knowledge, there is no study that investigates the moderating role of ER strategy on experienced gains or losses, and how these alter the course of EV-maximizing behavior. The second set of hypotheses can be stated as follows:

Hypothesis 1.3: Given a loss (gain), applying reappraisal strategies (a) reduces

(increases) the level of arousal experienced and (b) moderates the role of integral arousal leading to increased (decreased) EV-maximizing behavior.

Hypothesis 1.4: Given a loss (gain), applying suppression strategies (a) increases (reduces) the level of arousal experienced and (b) moderates the role of integral arousal leading to decreased (increased) EV-maximizing behavior.

3.3 Method

In order to investigate the above hypotheses, we employed a within-subject 2x2 factorial experimental design with a repeated trading decision scenario. Each subject participated in one practice round and 15 rounds of trading. In each trading round, the subject is endowed with four stocks, picked randomly in subsequent order. Each of these trials was then structured as follows: The participant started with an initial endowment of €100, and was provided with complete information on probability of price increase (PROB), and valuations (VAL), i.e., the expected amount of gain/loss, with two treatment levels each. These treatment levels for PROB and VAL were in accordance with previous studies (Loewenstein et al., 2008). We restricted to two levels each, in order to ensure a higher number of data points per treatment, as required of physiological experiments. Possible price increases were either €2 or €10, hitherto labelled as VAL_LOWER (€2) and VAL_HIGHER (€10); and probabilities of price increase were either 0.45 or 0.55, hitherto labelled as PROB_LOWER (0.45) or PROB_HIGHER (0.55). Table 3.1 summarizes the treatment structure.

		Valuation	
		Lower Valuation	Higher Valuation
Probability	Lower Probability	PROB_LOWER (0.45) VAL_LOWER (€2)	PROB_LOWER (0.45) VAL_HIGHER (€10)
	Higher Probability	PROB_HIGHER (0.55) VAL_HIGHER (€2)	PROB_HIGHER (0.55) VAL_HIGHER (€10)

TABLE 3.1: *Treatment Structure*

Based on stock information and the trend after one period, the subject then decided whether to hold or sell the endowed stock. After this decision, the stock's trend was shown for one more period, and if the subject held (sold) the stock after the first update, the second (first) update was counted in for the payoff in that trial. The stock was automatically sold after these two price updates. Appendix B illustrates the screenshots of the interface and the final trading screen. At the end of the experiment, exactly one trial was chosen by the subject by rolling a dice twice: once to choose the round number (1-15), and once to choose the stock (1-4). The profit in this trial was paid out in cash after the experiment. A trading decision scenario is described by providing complete information on expected monetary value in a path-independent manner. The trials vary only in whether the stock gained or lost in value; drawn from the probability of price increase for each period of trading. To ensure independence of trials, and uniform interpretation of provided data by participants, the following were controlled for:

- Participants were endowed with a stock in each trial to minimize the possible influences of previous stock trends. Hence, learning effects are minimized by creating a fresh reference value to the subject in each trial.
- To minimize false beliefs attached to a stock, participants were instructed that there would be no cumulative payoff, and that the payoff in each trial was equally likely to be drawn as the other, hence providing the incentive to trade in each round equally. This also controlled for belief updates that might otherwise occur during the course of the experiment.
- To assure minimum ambiguity, participants were provided the exact probability of price increase in each trial, and thus varying or hidden expected values were controlled for. This design element hence implicitly restricted participants from erroneously estimating the probability of price increase after experiencing a gain/loss (both within and across trials).

To ensure that affective cues resulting from the information was restricted to integral arousal, and not distorted by incidental arousal, noise-cancelling headphones were provided to the participants, to minimize distractions during the experiment.

3.3.1 Procedure

The experiment was conducted at the Institute of Information Systems and Marketing, Karlsruhe Institute of Technology in accordance with the university's ethics guidelines. At the beginning of each session, instructions were read out to all participants, providing them with general and specific information about the treatments. Participants completed a questionnaire consisting of 6 questions, in order to ensure understanding of the procedure. The stock game duration was close to one hour. At the end of the session, participants were asked to complete additional questionnaires. The experiment was implemented on z-Tree software (Fischbacher, 2007), while the questionnaires were implemented on Lime-survey in combination with hand-written text forms. The exact time (in milliseconds) of viewing information, decision-making, and events in each trial was logged on a per-client basis, in order to perform event-based analysis on the physiological data. One experimental session took about 1.5 hours, and in total, 100 subjects participated in 10 sessions (mean age = 22.59, male = 78, female = 22), with ten subjects each. Participants were recruited from a pool of students using the ORSEE software environment (Greiner, 2004). The experiment consisted of 10 sessions with ten participants each, and the recruitment system ensured that no subject attended more than one session. Subjects received a show-up fee of € 5, and earned on an average € 26.

During the duration of the experiment, participants' skin conductivity was recorded with Ag/AgCl electrodes (silver/silver chloride). These electrodes were attached on the thenar and hypothenar eminences of the palm of the non-dominant hand by use of standard electrodermal electrode paste. HR was measured using Electrocardiogram (ECG) electrodes, attached to the chest by means of single use ECG electrodes (Electrodes Ambu BlueSensor L). Sensor data from both modalities were recorded simultaneously by connecting the first two channels on the Bioplux (2007) system. Each session started with an initial five minute rest period, necessary for a proper calibration of the physiological signals. 15 subjects had to be excluded from the analysis because no adequate physiological measures could be assessed, resulting due to measurement sensors with weak or out-of-range signals with respect to SCR, or insufficient number of cases. All ECG measurements in this experiment were successful, and artefacts were detected using the standard linear time-series cleaning algorithm to detect gross artefact or noise, as per the recommendations by Clifford (2007). Hence the dataset consisted of 85 participants with complete SCR and HR measurements.

3.3.2 Measures

Questionnaires were used to assess demographic factors such as age and sex, participants' experience levels, impressions of the task, and any strategies they employed for the four treatment levels. This was followed by answering the emotion regulation questionnaire (ERQ) by Gross and John (2003) to assess the individual ER strategies employed. The ERQ consisted of ten questions (six for cognitive reappraisal and four for suppression), containing questions such as "When I want to feel more positive emotion (such as joy or amusement), I change what I'm thinking about" for measuring reappraisal, vs. "When I am feeling positive emotions, I am careful not to express them" for measuring suppression. Each question was encoded on a 7-point interval scale. Participants' ER strategy was computed by dividing subjects into reappraisers, if the average of their scores for the 6 reappraisal items, was greater than the population mean (of 4.2). Analogously, if the average of the scores for the 4 suppression items was greater than the population mean (of 3.5), they were marked as suppressors. Appendix B contains the complete set of questions of the ERQ employed in this study.

Finally, the risk aversion questionnaire by Holt and Laury (2002) was also employed to measure the variations in risk attitudes of participants, by means of 10-item coupled lottery task. Participants systematically marked their choices on these 10-items. Based on the crossover point (from 1-10) to the high-risk lottery, the degree of risk aversion can be inferred (5 being risk neutral, less than 5 being risk-averse, and greater than 5 being risk-seeking). Based on these, participants' risk aversion was dummy coded, indicating whether they were risk averse or not. Appendix B contains the complete risk aversion questionnaire employed in this study.

In order to observe deviations from EV-maximizing strategies with respect to the treatment variables, dependent variable was computed as follows. Irrespective of the valuation and whether the price increased or decreased in the first period, the EV-maximizing strategy space in this design was defined as: Sell, for PROB_LOWER, for both VAL_HIGHER and VAL_LOWER Hold, for PROB_HIGHER, for both VAL_HIGHER and VAL_LOWER Strictly speaking, this means that subjects should always sell, when a stock PROB_LOWER was drawn, and should always hold it when a stock PROB_HIGHER was drawn. Each decision was then compared with the EV-maximizing strategy space, to determine if it was an EV-maximizing decision or not.

For the physiological measures, Figure 3.1 depicts critical events related to this experiment, where the course of decision-making under risk was segmented to identify integral arousal, in tune with previous research (Bechara and Damasio, 2005; Adam and Kroll, 2012). Event E1 marks the information processing stage, where participants received information about the stake chosen (€ 2/€ 10), and the probability of price increase (0.45/0.55). At Event E2, participants received the first information update about the price (i.e. gain or loss), after which he/she decides to hold/sell the stock. The actual decision to hold/sell was made at E3. At E4, the participant received a second price update which could be processed differently, depending on whether the stock was held or sold.

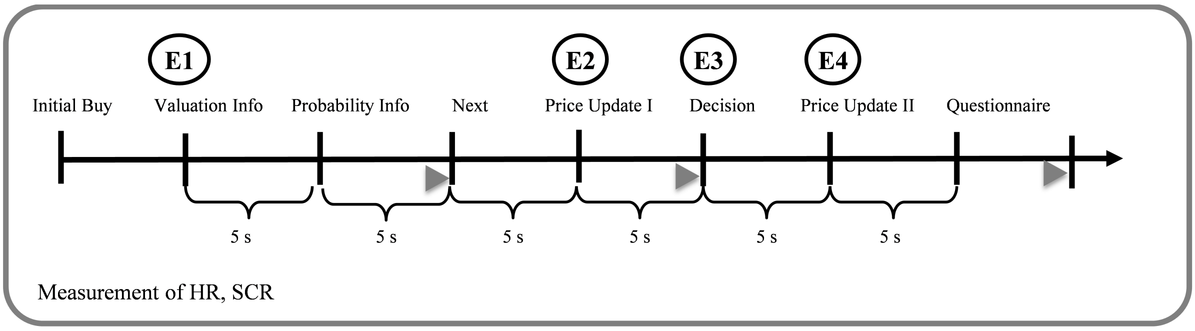


FIGURE 3.1: *Structure of a single round of decision making*

With respect to physiology, phasic changes in SCR and HR in response to the events enlisted above were focused upon. For the analysis, the amplitudes of monophasic SCR (SCR.amp) were computed as a measure for the intensity of integral arousal, 1-3 seconds before the event of interest (Boucsein, 1992). Following the recommendations of Fowles et al. (1981), all SCR.amp values x were than transformed according to $log(x+1)$ in order to reduce the inherent left skewedness of the SCR.amp. Between-subjects variability of SCR was reduced by normalizing the subjects' average response to the average amplitude of the two events E1 and E2 (before decision) and at E3 (at the point of decision-making). E4 was not taken into account since it takes place post-decision, and hence would fall under the category of expected emotion, whereas the hypotheses we pursue pertain to the role of ER strategy on integral arousal. Waning responses in HR were taken as a measure of parasympathetic activity. Analyzing phasic changes 5 seconds before each event allows an evaluation of the perceived valence in response to events such as experiencing a gain in the endowed stock. Analogously, we focused on the ECG within 5 seconds before each event, and assessed the magnitude of the deceleratory HR response by taking the difference with the average HR response in the initial cool down period. HR variability features were also computed in addition.

To summarize: the SCR features, the HR variability features, decrease in phasic HR were considered as proxies for studying the influence of integral arousal. In order to represent the information content of the various features resulting from these three types of features, a factor analysis method was applied to build a reduced arousal parameter, using the Principal Component Analysis (PCA) algorithm. The orthogonal method of feature space rotation (Varimax) was adopted to ensure that non-correlated features are rotated and represented along different dimensions (cf. Schutte et al., 1998; Shivappa et al., 2010, for a similar approach). The arousal parameter was built by considering features from both sensors, and from the significant events of interest before the decision. The significant event of interest was fixated upon E2, since this was the only event (among E1, E2, E3) that yielded a significant difference in heart rate, as revealed by repeated measures ANOVA for the two treatments PROB and VAL (Section 3.4). Similarly, SCR was calculated for event E2. The final two components depicted in Table3.2 were obtained after (1) comparing several reductions, (2) removing insignificant and correlated features: for example HFLF ratio, heart rate variability features calculated using Fast fourier transform, or the Lomb periodogram methods: for a detailed comparison see (Clifford, 2002), and (3) performing orthogonal rotation. The best method yielded two principal components (PC's) explaining up to 92% of the variance in data, and their factor loadings are depicted in Table3.2. Two factors are retained, one representing items from SCR (`SCR_Fac`) and one representing items from HR (`HR_Fac`),with one feature overlapping in Component 1. The factor loadings of these components were then used in the subsequent regressions, to represent the arousal parameter in the regressions depicted in Table3.3 - 3.5.

TABLE 3.2: *Factor loadings of physiological parameters with Varimax Rotation*

Feature	Description	Cronbach Alpha	Factor loadings for Component	
			Arousal_Fac_HR	Arousal_Fac_SCR
avghr_pre10	Normalized HR 1 s before event		**0.987**	0.133
avghr_pre9	Normalized HR .9 s before event		**0.987**	0.145
avghr_pre8	Normalized HR .8 s before event		**0.99**	0.12
avghr_pre7	Normalized HR .7 s before event		**0.992**	0.085
avghr_pre6	Normalized HR .6 s before event		**0.991**	0.117
avghr_pre5	Normalized HR.5 s before event	0.98	**0.991**	0.114
avghr_pre4	Normalized HR .4 s before event		**0.996**	0.044
avghr_pre3	Normalized HR .3 s before event		**0.997**	0.025
avghr_pre2	Normalized HR .2 s before event		**0.995**	0.045
avghr_pre1	Normalized HR .1 s before event		**0.995**	0.05
avg_cda_tonic	Mean tonic activity		**0.696**	-0.381
avg_cda_nscr	Number of significant SCRs		0.191	**0.967**
avg_cda_ampsum	Sum of SCR-amplitudes [muS]		-0.101	**0.952**
avg_cda_scr	Average phasic driver [muS]	0.85	-0.396	**0.888**
avg_cda_iscr	Area of phasic driver [muS*s]		-0.396	**0.888**
avg_ttp_latency	Response latency of 1st sign. SCR [s]		-0.337	**0.704**
Eigenvalue			10.915	4.704
Variance Explained (%)			63.6	28.27
Cumulative Variance (%)			63.6	91.87

Note: Average Phasic Heart Rate was computed in the time frame of 1s before E2.
SCR features were calculated using Ledalab (Benedek & Kaernbach, 2010) for Matlab on E2.

3.4 Results

Figure 3.2 depicts the distribution of fraction of EV-maximizing decisions over all decisions, from which it can be observed that participants were distributed predominantly between 0.6 and 1. Of the 100 participants, 57 of them were found be reappraisers while 58 were classified as suppressors (32 participants applied both these strategies, and 17 of them used neither of these strategies).

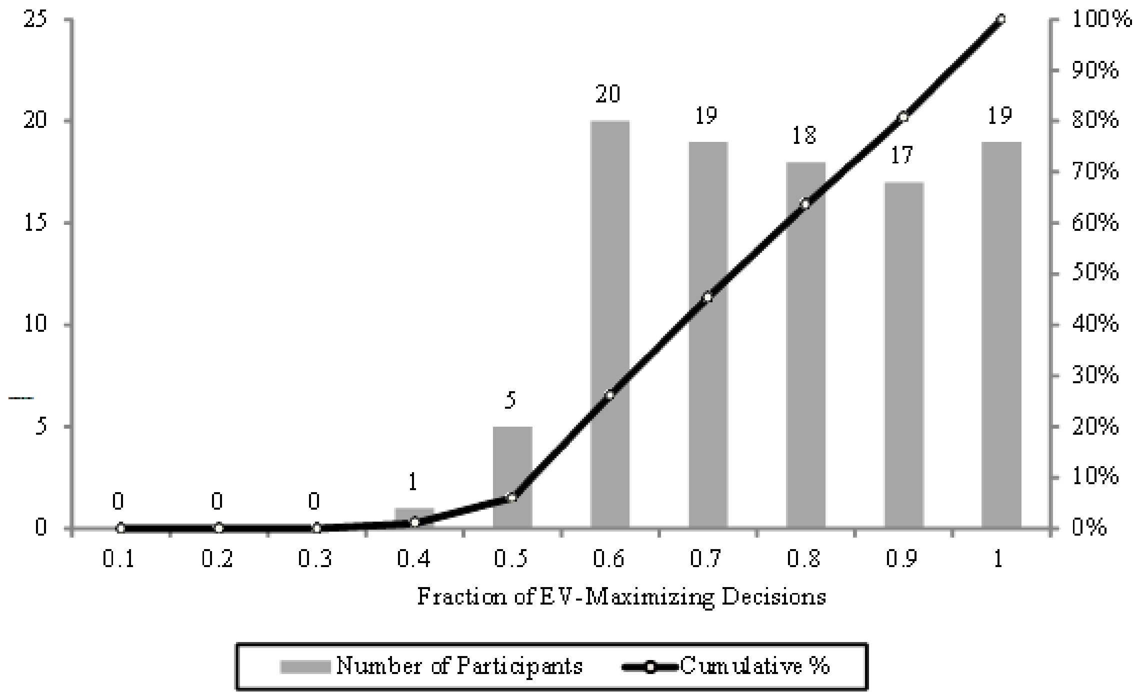


FIGURE 3.2: *Distribution of Fraction of EVM decisions taken by participants*

3.4.1 General Observations

Regressions in Tables 3.3 - 3.5 depict behavior regressed on economic indicators, physiological arousal and the ER strategies of a person (dummy variables to indicate whether he/she was a reappraiser or not, and whether he/she was a suppressor or not). H1.1 - H1.4 (a) are based on linear regressions with fixed effects for subject, while H1.1 - H1.4 (b) are based on mixed-effects logistic regressions on the binary dependent variable (if the decision made was EV-maximizing or not) with the independent variables as fixed effects and subject random effects. Expectedly, both the treatment variables PROB and VAL significantly explained participants' EV-maximizing decisions. All regressions further revealed that the interaction between the PROB_HIGHER and VAL_HIGHER term was a significant antecedent of participants' EV-maximizing decisions.

TABLE 3.3: *Effect of ER strategies on EV-maximizing decisions*

	Dependent variables					
	Arousal (HR) (1)	**Arousal (SCR) (2)**	**is_EVM_ decision (3)**	**Arousal (HR) (4)**	**Arousal (SCR) (5)**	**is_EVM_ decision (6)**
dummy_prob_higher	-0.034	0.006	0.984***	-0.034	0.007	0.982***
	(0.038)	(0.038)	(0.099)	(0.038)	(0.038)	(0.099)
dummy_val_higher	-0.041	-0.027	1.033***	-0.041	-0.027	1.026 ***
	(0.038)	(0.038)	(0.100)	(0.038)	(0.038)	(0.100)
dummy_prob_higher x dummy_val_higher	0.009	0.042	-2.218***	0.009	0.041	-2.216 ***
	(0.054)	(0.054)	(0.141)	(0.054)	(0.054)	(0.141)
arousal_ fac_hr			-0.169 (0.060)**			-0.192(0.070)**
arousal_fac_scr			-0.037(0.077)			-0.024 (0.08)
arousal_fac_hr x dummy_prob_higher			0.214(0.07)**			0.213(0.07)**
arousal_fac_scr x dummy_prob_higher			0.072 (0.076)			0.056 (0.073)
arousal_fac_hr x dummy_val_higher			0.04 (0.07)			0.042 (0.07)
arousal_fac_scr x dummy_val_higher		0.009(0.077)			-0.019(0.072)	
is_reappraiser	-.082 ***	-.204 ***	0.092			
	(0.027)	(0.027)	(0.277)			
arousal_fac_hr x is_reappraiser			0.220(0.124)*			
arousal_fac_scr x is_reappraiser			-0.244 (0.165)			
is_suppressor				-0.022	.135***	0.153
				(0.027)	(0.027)	(0.274)
arousal_fac_hr x is_suppressor						0.049 (0.079)
arousal_fac_scr x is_suppressor						-0.059 (0.082)
Constant	.083 ***	.117 ***	0.903***	0.047	-.072**	0.883 ***
	(0.031)	(0.031)	(0.217)	(0.031)	(0.031)	(0.207)
Log Likelihood			-2703.011			-2704.403

Note: N= 5420, Number of Groups = 85, Observation per group: Min. = 57, average= 63.8, max = 64. Regression coefficients with standard errors in parentheses. H1.1a and H1.2a are based on linear regressions with fixed effects for subjects (Regressions 1,2,4,5); H1.1b and H1.2b are based on mixed-effects logistic regressions on the binary dependent variable (if the decision made was EV-maximizing or not) with the independent variables as fixed effects and subject random effects (Regressions 3, 6). + p<.10; * p < .05; ** p < .01; *** p < .001

To account for the emotional arousal during the task, the SCR.amp and decreases in HR were examined at all events (E1-E3) before the decision, taken treatment-wise. As mentioned earlier, data at E4 was not studied in this context, since it occurred post-decision. A repeated measures ANOVA revealed that higher valuations resulted in an increase in SCR.amp ($F(1, 88) = 28.254$, $p<0.001$) before event E2 when subjects processed information about the first price change. The decision to sell revealed lower amplitudes than the decision to hold ($F(1, 33) = 8.298$, $p<0.01$). However, at event E3, it was more difficult to differentiate if the physiological response is caused by the treatment factors or by the decision just taken and hence, the responses at/immediately before event E3 would be a noisy estimator of the EV-maximizing decision. A similar repeated-measures ANOVA for the average decrease in phasic heart rate 1 second before each event revealed that heart rate was significantly explained by the valuation ($F(1,89) = 28.196$, $p<.001$). At E3, heart rate was significantly explained by the interaction of VAL_HIGHER and PROB_HIGHER ($F(1, 32) = 5.307$, $p<0.05$), and the decision to sell ($F(1, 32) = 4.883$, $p<0.05$). For similar reasons to the ones previously stated, the explanation for the changes in the heart rate cannot be without noise from the decision at hand, and hence it could not be taken in as a factor to predict the EV-maximizing decisions. Hence, for the further hypotheses, the differences in physiology between the treatments only at event E2 were focused upon. Figure 3.3 depicts the normalized SCR.amp, and Figure 3.4 depicts the decrease in HR, for the VAL treatment at event E2 averaged across all participants. Taken together, it could be confirmed that the treatment factor of higher valuations led to an increased SCR at event E2.

3.4.2 Influence of Emotion Regulation

Regressions for H1.1a and H1.1b in Table3.3 accounted for the effect of reappraisal strategy on experienced arousal level, and the moderating role of reappraisal on the arousal factors, respectively. Assuming dummy variables for whether a person was dominantly a reappraiser or not, regressions (1) and (2) in Table3.3 showed that reappraisers experienced lower levels of HR (B=-.082, SE=.027) and lower levels of SCR (B=-.204, SE=.027). Hence, this confirms H1.1a that reappraisers tend to experience lower levels of integral arousal, as measured by heart rate and skin conductance. Testing H1.1b, Regression 3 showed that the strategy of reappraisal moderated the heart rate arousal parameter (Arousal_Fac_HR) and led to significantly more EV-maximizing decisions (B=0.220, SE=.124), thus confirming H1.1b. In other words, applying reappraisal strategies mod-

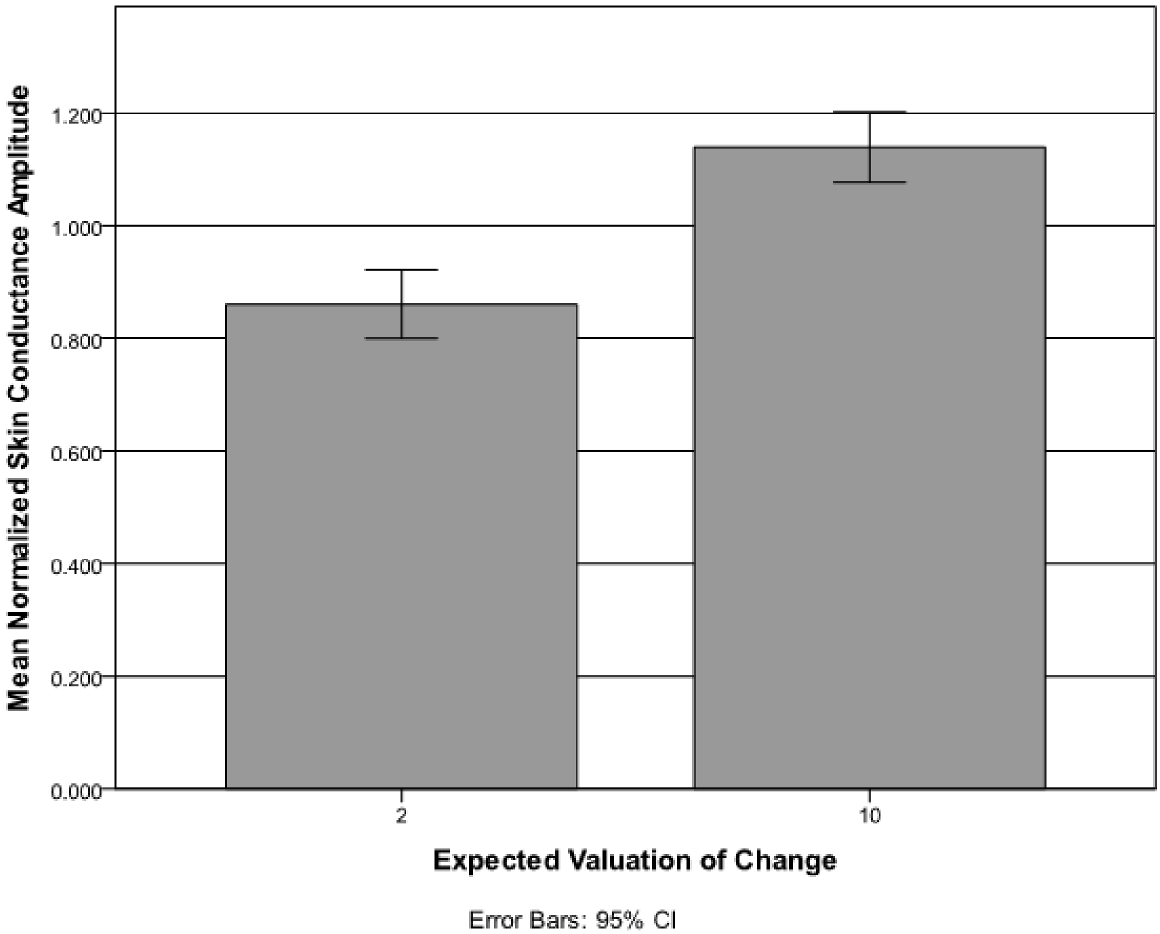


FIGURE 3.3: *Normalized Skin Conductance Response for Price Change Event*

ifies the extent to which integral arousal impacts EV-maximizing behavior, in this case, reappraisers exhibit more EV-maximizing behavior, possibly due to the arousal levels associated.

From the regressions (4-6) for H1.2a in Table3.3, the results showed that suppression did not significantly impact the level of heart rate, while the level of experienced SCR was significantly higher (B=.135, SE=.027) than for non-suppressors. Further, as shown in Table3.3, suppression did not significantly moderate the role of arousal on EV-maximizing behavior, thus invalidating H1.2b.

The above results are well in line with previous findings on the positive influence of reappraisal strategy in trading contexts (Fenton-O'Creevy et al., 2012). These regressions (Table3.3 - 3.5) bring to light that it is hence valuable to control for affective responses and ER to understand EV-maximizing behavior.

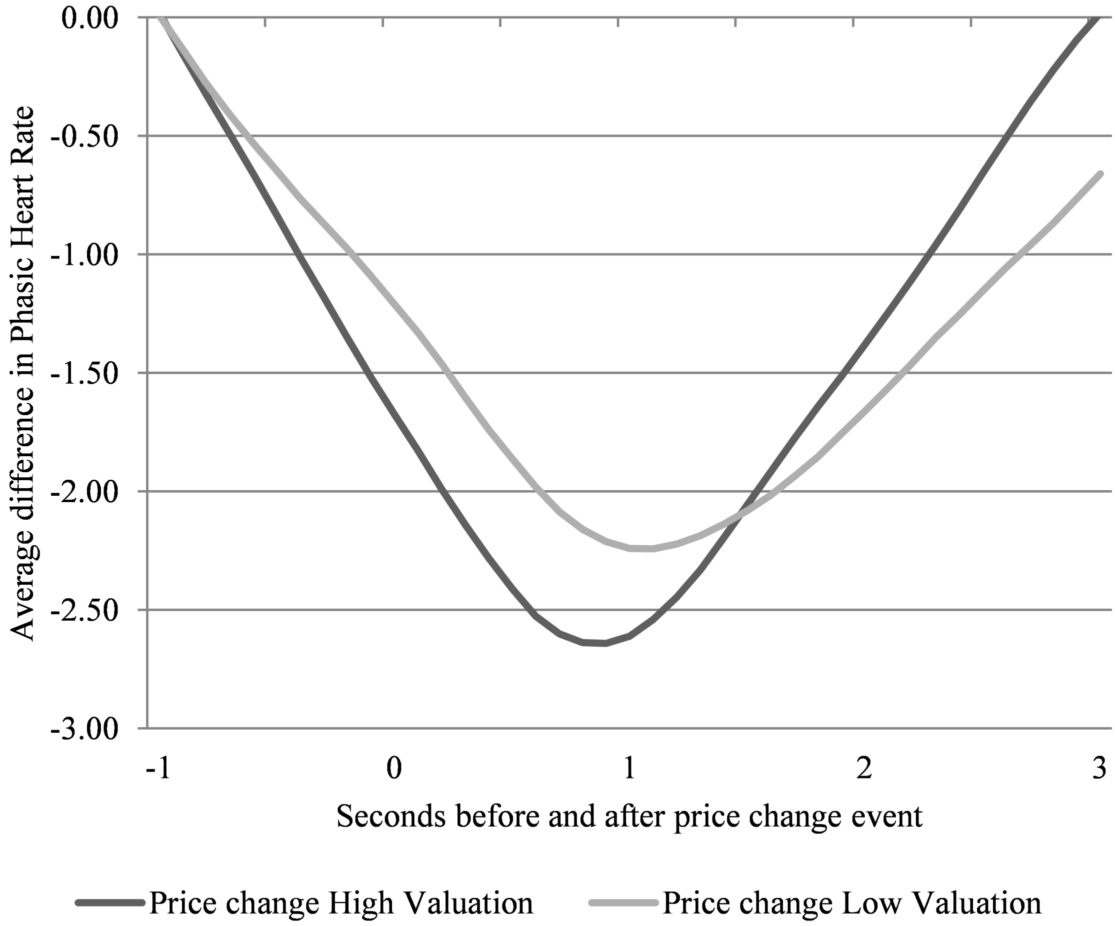


FIGURE 3.4: *Differences in heart rate for Price Change Event*

We next examine, in the context of whether a gain or loss occurred in the first trading round, and whether subjects were reappraisers or suppressors or not (H1.3, H1.4), and how these conditions influenced the level of arousal and the EV-maximizing behavior. As seen in Regression 3 in Table 3.4, given a gain in the first round, reappraisers experienced a lower level of SCR (B=-.177, SE=.035). Given a loss (Regression 2 & 4) in the first round, both heart rate measures (B=-.150, SE=.038) and SCR (B=-.230, SE=.042) were significantly lower for reappraisers. The above results confirm H1.3a that reappraisers experience lower levels of arousal, given a loss. For gains, however, whereas theory predicts that reappraisers have an increased level of arousal, the data showed otherwise. These results point in the direction that, irrespective of the gains and losses experienced, reappraisers tend to have a lower level of arousal. Secondly, turning to H1.3b, regression 6 in Table3.4 shows that given a loss in the first round, reappraisal interacts with HR arousal leading to more EV-maximizing behavior (B=0.401, p=0.034), hence confirming the first part of H1.3. Similar significant moderating effects on arousal were not observed for reappraisers, given a gain in the first round (Regression 5). Finally, Regressions 9 and 10 in Table3.5 reveals that suppressors experienced a higher level of SCR, for both gains and losses. This result, although indicative of a difference in arousal level for suppressors, and hence confirming H1.4a, is in the opposite direction as predicted by theory. No such differences in heart rate were observed for suppressors, after experiencing a gain or a loss. Moreover, the moderating effect of suppression strategies on arousal was not significant in the context of gain or loss (Regressions 11 and 12), thus providing no support for H1.4b.

In order to validate the above hypotheses further, risk attitudes were controlled for by using the risk-aversion questionnaire (Holt and Laury, 2002). However, risk aversion did not significantly moderate the impact of the two arousal parameters, or the ER strategies, and hence did not increase the explanatory power. Finally, controlling for gender, no significant direct or moderating role on arousal or on EV-maximizing decisions either was found, showing robustness against controlling for possible gender effects.

3.4.3 Attraction to Chance

When gambles that involve possible gains are presented one at a time most people display a level of appeal towards the gambles. The phenomenon of gaining satisfaction directly from the riskiness of the situation has been termed as the *attraction to chance*, and of suffering dissatisfaction directly from the riskiness of the situation, *repulsion from chance* (Albers et al., 2000). Adam and Kroll (2012) established through experiments with physiological measurements that attraction to chance can be explained by differences in emotions that subjects experience based on the choices made by people for different types of lotteries.

In situations of low stakes and low probability to win, we observe the behavioral bias wherein: participants are exposed to "attraction to chance," for which we also report physiological indication in the following. Table3.6 summarizes the number of hold decisions taken by participants, treatment-wise. It is worth noting that there was a significant difference in the scores for number of held decisions in the VAL_LOWER (M=6.282, SD = 4.520) and VAL_HIGHER (M=3.729, SD = 3.279) when considering the treatment of PROB_LOWER (t (69) = 3.969, p<.001). These decisions are quite out of the ordinary, especially in the presence of complete information on the probability of winning. In fact, it illustrates the phenomenon of attraction to chance, which could be seen/interpreted as the

TABLE 3.4: *Effect of reappraisal strategy on (a) experienced arousal (b) EV-maximizing decisions, after a gain/loss in the first round*

	Dependent variables					
Independent variables	**(H1.3a) arousal_fac_hr**		**(H1.3a) arousal_fac_scr**		**(H1.3b) is_EV_ maximizing_decision**	
	Gains(1)	**Losses(2)**	**Gains (3)**	**Losses(4)**	**Gains (5)**	**Losses (6)**
dummy:prob_higher	-0.05 (0.055)	-0.02 -0.053	-0.018 (0.049)	0.031 (0.059)	.527*** (0.143)	1.447 *** (0.145)
dummy:val_higher	-0.047 (0.055)	-0.037 (0.053)	0.019 (0.049)	-0.073 (0.059)	.774*** (0.149)	1.254 *** (0.141)
val_higher x prob_higher	0.002 (0.078)	0.015 (0.076)	-0.019 (0.069)	0.101 (0.083)	-1.67*** (0.204)	-2.75 *** (0.204)
arousal_fac_hr					-0.094 (0.085)	-.232 ** (0.088)
arousal_fac_scr					-0.008 (0.116)	-0.053 (0.106)
arousal_fac_hr x dummy:prob_higher					0.109 (0.101)	.334 ** (0.101)
arousal_fac_scr x dummy:prob_higher					0.008 (0.16)	0.114 (0.101)
arousal_fac_hr x dummy:val_higher					0.139 (0.102)	-0.039 (0.101)
arousal_fac_scr x dummy:val_higher					0.034 (0.156)	-0.003 (0.101)
is_reappraiser	-0.012 (0.039)	-.150*** (0.038)	-.177 *** (0.035)	-.230*** (0.042)	-0.062 (0.291)	0.137 (0.282)
arousal_fac_hr x is_reappraiser					0.107 (0.18)	.401 * (0.19)
arousal_fac_scr x is_reappraiser					-0.191 (0.284)	-0.341 (0.208)
Constant	0.067 (0.045)	0.098 (0.044)	0.087 (0.04)	0.147 (0.048)	-0.037 (0.041)	0.588 (0.225)
Log Likelihood					-1321.237	-1381.536

N= 5420, Number of Groups = 85, Observation per group: Min. = 57, average= 63.8, max = 64. Note. Regression coefficients with standard errors in parentheses. + p<.10; * p < .05; ** p < .01; *** p < .001

TABLE 3.5: *Effect of suppression strategy on (a) experienced arousal (b) EV-maximizing decisions, after a gain/loss in the first round*

	Dependent variables					
Independent variables	**(H1.4a) arousal_fac_hr**		**(H1.4a) arousal_fac_scr**		**(H1.4b)is_EV_ maximizing_decision**	
	Gains (7)	**Losses(8)**	**Gains (9)**	**Losses (10)**	**Gains (11)**	**Losses (12)**
dummy:prob_higher	-0.05 (0.055)	-0.021 (0.054)	-0.018 (0.049)	0.033 (0.059)	.522*** (0.143)	1.445*** (0.145)
dummy:val_higher	-0.047 (0.055)	-0.036 (0.054)	0.019 (0.049)	-0.072 (0.059)	.770 *** (0.148)	1.239*** (0.141)
val_higher x prob_higher	0.001 (0.078)	0.014 (0.076)	-0.025 (0.069)	0.109 (0.083)	-1.667*** (0.204)	-2.743*** (0.204)
arousal_fac_hr					-0.078 (0.095)	-.304** (0.104)
arousal_fac_scr					-0.027 (0.125)	-0.025 (0.118)
arousal_fac_hr x dummy:prob_higher					0.11 (0.101)	.338** (0.101)
arousal_fac_scr x dummy:prob_higher					-0.013 (0.157)	0.094 (0.101)
arousal_fac_hr x dummy:val_higher					0.142 (0.102)	-0.032 (0.101)
arousal_fac_scr x dummy:val_higher					0.018 (0.154)	-0.039 (0.096)
is_suppressor	0.014 (0.039)	-0.054 (0.038)	.105 *** (0.034)	.169*** (0.042)	0.223 (0.286)	0.122 (0.277)
arousal_fac_hr x is_suppressor					-0.04 (0.112)	0.142 (0.113)
arousal_fac_scr x is_suppressor					0.029 (0.138)	-0.064 (0.114)
Constant	0.054 (0.044)	0.042 (0.043)	-0.068 (0.039)	-0.079 (0.047)	1.166 (0.225)	0.609 (0.216)
Log Likelihood					-1321.143	-1383.485

N= 5420, Number of Groups = 85, Observation per group: Min. = 57, average= 63.8, max = 64. Note. Regression coefficients with standard errors in parentheses. + p<.10; * p < .05; ** p < .01; *** p < .001

emotional gratification derived from making a risky choice. Specifically, subjects choose to hold a stock in the case of low probability of price increase and a low stakes stock, even when the outcome is not as would be expected under EUT. We next test additionally, if there is physiological indication for attraction to chance observed before the "hold" decision in PROB_LOWER, VAL_LOWER treatment. A paired sample t-test revealed that at E1 participants differed significantly in SCR.amp ($t(69)$=2.344, p=.020) between their hold and sell decisions (Table3.7). However, during E2, the SCR.amp is not significantly different between hold and sell decisions for the PROB, or the VAL treatment. This observation points in the direction that while the anticipatory emotion before a hold and sell decision is not significantly different when viewed treatment-wise, attraction to chance manifests itself more clearly at event E1, when subjects receive the information about the stock, and decide to hold or sell the stock. At event E2, subjects seem to experience a sense of reality due to the first price update, leaving them possibly "less attracted to chance," which explains why this event did not provide a potential explanation for the difference between hold and sell decisions.

TABLE 3.6: *Mean number of hold decisions*

PROB	VAL	Mean number of held decisions
0.45	€2	6.282 out of 16 decisions
0.45	€10	3.729 out of 16 decisions
0.55	€2	13.343 out of 16 decisions
0.55	€10	9.939 out of 16 decisions

TABLE 3.7: *Paired sample t-test for SCR: held vs. sold stocks, for the (€2, 0.45) stock type*

Paried variables	t-stat	Sig	
E1:Held vs. sold	2.344	0.02	*
E2:Held vs. sold	1.393	0.164	
E3:Held vs. sold	0.582	0.561	
E4:Held vs. sold	1.412	0.159	
N=100, Note.*$p < .05$			

3.5 Discussion

In this chapter, we aim to further our understanding on deviations from EV maximization in a trading context, by studying the direct and the moderating role of ER strategies on emotional arousal and on EV-maximizing behavior, respectively. We hypothesize that adopting different ER strategies are accompanied by different levels of integral arousal, and has a significant moderating role on integral arousal, in explaining deviations from behavior as defined by expected-value maximization. To this end, a single-decision trading experiment is implemented, along with questionnaires and physiological measures.

The results reveal significantly lower levels of integral arousal (HR and SCR) for reappraisers (H1.1a), and higher levels of integral arousal (SCR) for suppressors (H1.2a). Also, the moderating effect of reappraisal strategy on arousal significantly increased the EV-maximizing behavior (H1.1b). A similar moderating effect of suppression was however, not significant (H1.2b). Also, only heart rate was moderated by the ER strategy leading to EV-maximizing behavior, whereas the SCR factor was not visibly influenced. This is an indicator that ER acts as a coping strategy in down-regulating valence particularly, and less efficient in down-regulating arousal.

Another interesting observation is that reappraisal has a significant moderating impact on arousal to explain EV-maximizing behavior, whereas suppression has no impact. These imply that reappraisal (i.e., cognitively altering the experience of emotions) is likely to be indicative of an increased affective awareness or an increased affective control, and hence plays a significant role on the relationship between emotional arousal and EV-maximizing behavior. In other words, while arousal leads to less EV-maximizing behavior for non-reappraisers, arousal actually turns out to be beneficial for reappraisers: the more aroused a reappraiser, the higher his/her likelihood of EV-maximizing decisions. These results are in tune with Heilman et al. (2010), wherein reappraisers reported reduced negative affect, further confirmed by Yang et al. (2014), who report that implicit emotion regulation effectively modulated the subjective affective experience.

Clearly, the strategy of suppression is not advantageous, and in fact has even shown to have detrimental effects on task performance in the above studies. Our results offer evidence that suppressors experienced an increased level of SCR, in both the context of gains and losses (H1.4a). Suppression did not play any role in altering the impact of emotions on EV-maximizing behavior, given a loss or a gain (H1.4b). This may be the case as suppression does not pertain to altering, but rather to inhibiting the experience of emotions and that the present study deals with consequentialist emotions prior to decisions (integral arousal). Another opportunity could be that suppression-as it occurs after an emotional response is generated-affects only counterfactual emotions, i.e., regretting a decision, or thinking about "what-could-have-been" after the consequences of the taken decision are experienced.

Previous studies have indicated that suppression of a thought results in an immediate increase of the frequency of this thought and/or in a rebound effect, i.e. in a heightened frequency of this thought later on (Muris et al., 1992). Hence, suppression is not necessarily an advisable strategy in this context, since it is likely to resurface at an inappropriate point in time with high intensity, potentially resulting in detrimental effects on behavior.

When it comes to the long-term effects of ER (i.e., the changes in employing specific strategies accompanied with aging), self-report evidence shows an age-related shift away from the response-focused strategy of emotional suppression toward the antecedent-focused strategy of reappraisal, which appears to be more efficient and less cognitively demanding (John and Gross, 2004). This is especially so, since suppression requires more cognitive effort, and with aging, people develop the skills to allocate their cognitive resources more efficiently, i.e., avoiding negative stimuli or avoiding excessive use of cognitive resources by suppression. While these long-term changes in emotion regulation with aging are not visible in our sample group, consisting only of university students, replicating our study with senior participants would throw further light on (i) the tendency to apply suppression in a decision-making context as a strategy in advanced age and (ii) whether there is a significant impact of suppression on outcomes. The cognitive effort involved, combined with the above-mentioned rebound effect, should make suppression a disadvantageous strategy for EV-maximizing behavior. However, further research is necessary, to investigate whether suppression in itself manifests as an intense physiological reaction consistently affecting behavior.

The impact of reappraisal is significant for situations of loss, which is not observed as strongly for situations of gain (H1.3a). This result suggests that cognitive reappraisal of negative emotion is not only feasible, but could also be beneficial, suggestive of a coping mechanism that traders/private investors should be trained to practice. The most relevant example to this end is the disposition effect, coined by Odean (1998), which highlights the tendency of traders to hold their losses too long, and to sell their gains too soon. This effect stems from the inability of traders to deal with losses, which according to the results of this study, can be trained by use of reappraisal strategies. As illustrated by Astor et al.

(2013a), psychophysiological measures could additionally validate if the training is indeed effective, and if participants are able to achieve better decision-making performance (in this case auctions), by using suitable reappraisal-inducing techniques.

Research on the coherence of emotion regulation and the "dual system" models (System I: consisting of the automatic, affective system and System II: consisting of the deliberative, cognitive system) in the context of decision-making is scarce (Lieberman, 2007). It appears possible that deliberative strategies that are required by the ER strategy of suppression (analogous to System II processes), are not necessarily associated with better outcomes in terms of EV maximization. Reappraisal on the other hand, makes more cognitive resources available, and providing the potential to lead to more EV-maximizing decisions. This is especially true of emotionally demanding situations, where System II resources need to be used in order to perform the task, and when these resources are not available due to the ER strategy employed, it leads to less EV-maximizing behavior. This is a possible explanation for the underlying relationship between ER and the dual processing theory, but remains an intriguing topic, that will have to be examined in future research.

In the presence of a loss, the modality of HR has been moderated by reappraisal leading to more EV-maximizing decisions (H1.3b). If HR were assumed as a proxy for valence, this indicates that reappraisal moderates negative emotions leading to more EV-maximizing decisions. Hence in debiasing, the quality of emotion (not only the arousal, but also the valence of emotion) that is debiased needs to be considered.

3.6 Limitations and Future Work

This chapter provides a research model that tests whether ER strategies moderate the role of emotions in EV-maximizing behavior. Nevertheless, there are limitations that need to be addressed in further work. In this experiment, based on previous work (Weber and Welfens, 2008), we specified two levels of probabilities and valuations. Whereas this design was successful in eliciting responses for higher and lower levels of treatment variables, it would be interesting to investigate this study with more probabilities, to determine whether the choice of probability might have an impact on how participants emote, regulate their emotions, and behave. Moreover, this study focusses on the decision problem in a granular level to understand deviations from EV maximization. These observations will have to be extrapolated on continuous trading data, in order to further verify and validate them. Also, it has been shown in continuous trading that, participants' reference levels shift across a given span of time, depending on their most recent profits and gains (Barber and Odean, 2001). In order to have a consistent reference point to compare the treatments of VAL and PROB; this aspect has been controlled for in this study by design. By means of field experiments, this aspect of continuous re-referencing and the impact of ER strategies on EV-maximizing behavior would have to be studied further. Moreover, ER strategies were not exogenously assigned in this context, and hence, in order to verify for potentially correlated individual characteristics that moderate the role of integral arousal on EV-maximizing behavior, the study will have to be replicated with exogenously assigned strategies. Finally, the finding that reappraisers (suppressors) experience lower (higher) levels of integral arousal should be examined more closely and verified in different contexts.

3.7 Conclusion

Turning to the research question RQ1 posed in the beginning of this chapter, it can be seen that, in an individual decision context, emotion-regulation strategies indeed moderate the role of integral arousal on EV-maximizing behavior. This is illustrative, that emotion impacts behavior, depending on whether a person reappraises his emotions or suppresses them. This brings to light, that the role of emotions on behavior, is dependent on individual differences in emotion regulation, and this needs to be carefully dealt with, while understanding decision processes involving information, and external events, in this case, of gains and losses. Specifically, the significant role of reappraisal, particularly in dealing with the external influences of gains and losses, has been observed in this study, illustrating that external influences manifest as internal influences on behavior. Hence, we argue that incorporating affective processes, along with individual differences in processing affect (i.e., the emotion regulation strategy), is a critical link for understanding the impact of events that occur during the course of a decision-making process.

In understanding the emotional underpinings of decision processes, we focused on the case of traders, where the cost of making decisions is high, justifying why their decision processes need to be well understood. However, what we learned from this study, is that the impact of the internal process of affect on behavior, is heavily dependent on a measurable attribute of a person, namely the emotion regulation strategy, and additionally so, when an external event such as a gain or a loss is experienced. This suggests that, the seemingly rational factors (in this case, the expected value of a decision) are dependent on the arousal experienced by the decision-maker. This particular result hence opens the possibility to a broader set of questions, moving from the case of the trader as a decision-maker, to that of a consumer, to further our understanding of decision processes. The first question amongst them is, are these results applicable in a decision context, wherein individuals are not only deciding on the basis of information presented to them, but in the presence of other decision-makers (i.e., a group setting)? We hence undertake the case of auctions, where consumers are the decision-makers, and which involves elements of competition. The decision process in this case, is one of bidding optimally, minimizing the cost paid, but being able to win the auction at the same time.

The second question that opens up, as a result of this chapter, could be stated as follows. Given that reappraisal is by definition a cognitive strategy, involving deliberatively altering the way one thinks about a situation - is there more at play, as to when and why arousal impacts behavior? In other words, is it possible, that, in order to understand affect, one has to consider whether and how cognition impacts decision-making, along with the influence of affective processes? If this were the case, how are the two processes (of cognition and affect) acting, based on external influences? In the following chapter, we explore in greater detail the following: whether the influence of internal processes (of cognition and affect) on behavior is dependent on specific economic external factors (such as the auction dynamics, and the information uncertainty associated with the value of a product), and if so, to what extent. We hence study the case of auctions, and how the processes of emotions and cognitive demand, impact optimal bidding.

Chapter 4

Cognitive and affective processes in auction bidding

> "There can be no knowledge about emotion. We may be aware of a truth, yet until we have felt its force, it is not ours. To the cognition of the brain must be added the experience of the soul."
>
> ARNOLD BENNETT (1867-1931)

4.1 Introduction

Everything starts in the mind. The most profound of philosophical thoughts to the most mundane of activities stem from the human brain, making humans highly mental creatures. Due to a heavy dependence on the decisions we make, we are well advised to constantly watch and control our mind in order to handle positive and negative events alike. While this undoubtedly holds for private life, it has shown to extend to markets in general (Lerner et al., 2004) and electronic markets in particular (Adam et al., 2011). Auctions are frequently used market mechanisms for determining resource allocation and prices in markets around the world. Prominent examples include spectrum license auctions (Kroemer et al., 2016) , the Dutch flower market, and Internet consumer auctions such as eBay and DealDash (Ariely and Simonson, 2003; Adam et al., 2012a). To inform the design of such markets, economic theory provides a rich set of models for understanding the behavior of auction participants and how they reflect different parameters of the auction environment in their bids (Kagel and Levin, 1986, 2002). However, auction theorists have raised important questions regarding the nature of the decision processes underlying human bidding behavior, as empirical studies repeatedly provide evidence that human bidders deviate from the theoretically derived optimal bid functions (Rothkopf and Harstad, 1994; Kambil and van Heck, 2004). In this chapter, we particularly focus on two parameters of the auction environment, namely auction dynamics and value uncertainty, which have been found to be key determinants of bid deviations.

First, auctions may differ in the extent of auction dynamics, e.g., caused by different time constraints for placing a bid. For instance, Dutch auctions start with a high price, which is dynamically decreased until one of the bidders places a bid, thus accepting to buy the good at that price and ending the auction. In contrast, in first-price sealed-bid auctions (FPSB), all bidders submit their bids simultaneously by a concealed method, usually without explicit time pressure. The bidder with the highest bid wins the item and pays their bid. While the two auction formats are strategically equivalent from a theoretical perspective (McAfee and McMillan, 1987), applying different formats in practice has shown to yield differences in behavior (Katok and Kwasnica, 2008; Adam et al., 2012a). Second, within an auction for a specific good, there may exist different levels of value uncertainty about the true value of the good (such as for spectrum licenses), which has direct ramifications for determining the optimal bid. Factors like strategic considerations, risk preferences, and the inherent selection mechanism of auctions (i.e., the risk of biased information, also known as the "winner's curse") are often at work simultaneously in influencing whether and how bidders might deviate from optimal bids.

It is widely accepted that decisions depend on cognitive as well as affective demands (Agarwal and Malhotra, 2005; Turel et al., 2011). In a simplified conceptualization, the mind can be broken down into the above two components, brought together within dual processing theory (Lieberman, 2007). In the context of auction bidding, both systems may be involved, i.e., cognitive workload (van den Bos et al., 2008) as well as emotional arousal (Adam et al., 2012a) in influencing bidding behavior. The impact of the internal processes on bidding behavior, however, is affected by the external auction environment in which the decision-maker is placed in. On the one hand, bidders might experience emotional arousal in anticipation of submitting a bid or while winning/losing an auction (Teubner et al., 2015; Adam et al., 2015). On the other hand, auctions also confront bidders with a puzzle-like task, in which considering aspects such as the auction format, other bidders' bids, and value uncertainty is essential for placing optimal bids. Hence, auctions necessitate significant cognitive effort before making a decision. From a market design perspective, and also from the perspective of market participants, it is valuable to understand whether and how the auction environment determines the impact of the internal processes (of cognitive workload and emotional arousal) on bidding behavior, in terms of deviations from the optimal bid. The research question addressed in this chapter is:

RQ2:In a group context, to what extent is the relationship between cognitive and affective processes and bid deviations determined by auction dynamics and value uncertainty?

To address this question, an auction experiment was designed and conducted with 39 participants. By varying two aspects of the auction environment, namely auction dynamics and value uncertainty, we measure the cognitive workload and emotional arousal, and how these processes are correlated with bidding behavior, assessed in comparison to the optimal bid Kagel.1986,vandenBos.2013. In order to measure cognitive workload during the task, a self-reported scale (NASA-TLX, Hart (1988)) and a physiological scale (Electroencephalography, EEG) were used. Emotional arousal was measured using phasic heart rate changes throughout the experiment, in accordance with the recommendations of NeuroIS methodologies, as proposed by Riedl et al. (2014).

Our results show that higher auction dynamics increase the role of emotional arousal to lead to larger deviations from the optimal bid, but not that of cognitive workload. High value uncertainty, in contrast, significantly increases the role of cognitive workload, leading to larger deviations from the optimal bid, but not that of emotional arousal. The remainder of the chapter is structured as follows: Section 4.2 outlines theoretical background and related literature, developing the hypotheses. Section 4.3 depicts the experimental design, methodology, and measures employed, followed by the results and analyses in Section 4.4. Section 4.5 discusses implications, limitations, and directions for future research.

4.2 Theoretical Background

To understand and to predict the behavior of auction participants, economists have proposed optimal bid functions based on specific assumptions about the bidders (e.g., riskneutrality, Kagel Levin, 1986). However, there is evidence that bidders systematically deviate from such optimal bid functions, e.g., due to competitive arousal (Ku et al., 2005), expected regret (Astor et al., 2011), agency (Teubner et al., 2015), or pseudo-endowment (Ariely and Simonson, 2003). In this regard, deviations from the optimal bid represent a measure as to how bidders are affected by the specific conditions of an auction environment. To assess participants' bidding behavior, in this study we thus examine bid deviations (ΔB) from the optimal bid. Based on theoretical and empirical literature, we first outline how emotional arousal (EA) and cognitive workload (CW) might be associated with bid deviations. We then develop hypotheses as to why and how these associations may be moderated by the treatment variables auction dynamics (AD) and value uncertainty (VU). Figure 4.1 connects all factors and hypotheses in a concise research model.

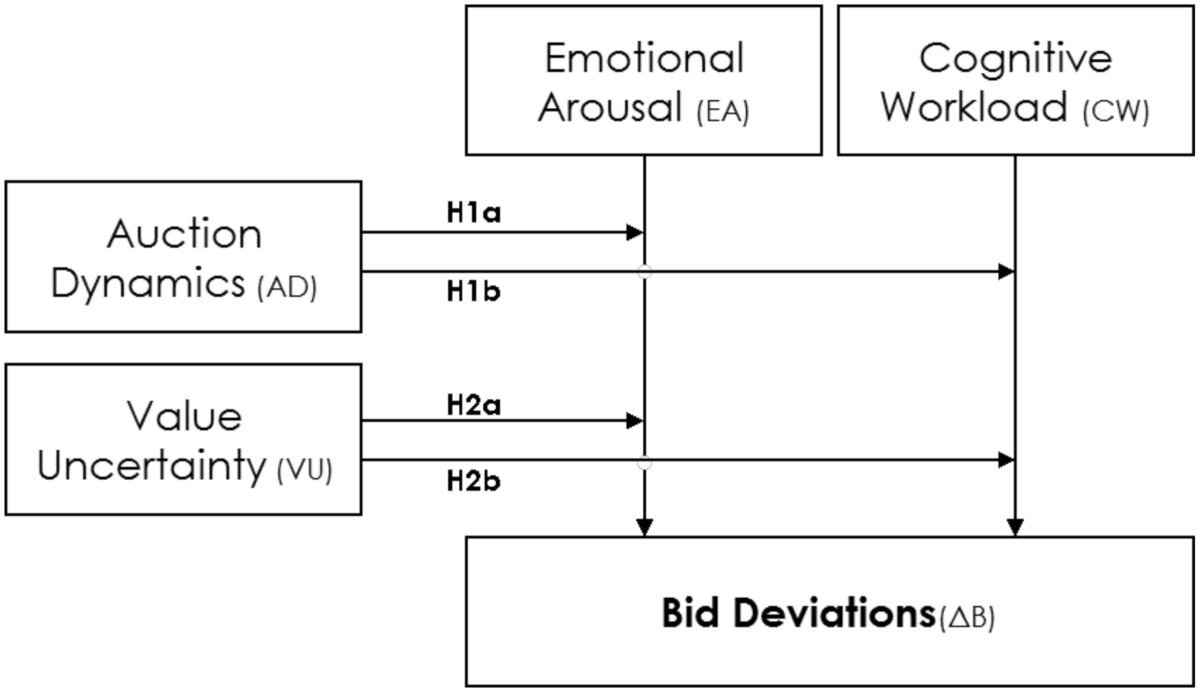


FIGURE 4.1: *Research Model*

4.2.1 The Influence of Emotional Arousal and Cognitive Workload on bid deviations

The dual process model of decision-making, with the distinction of decision-making into affective and cognitive processes, is a useful simplified scheme to analyze arousal and cognitive workload related aspects as determinants of choices (Lieberman, 2007). In the context of economic decision-making and auction bidding in particular, emotions have been distinguished as anticipated and integral emotions (Loewenstein, 2000; Adam et al., 2011). It has been shown that anticipated emotions impact decisions to a large extent, since they could decide if the intention to bid actually translates into action. Engelbrecht-Wiggans and Katok (2008) further illustrated the above point and distinguished winner and loser regret. Anticipated emotions of regret were shown to lead to lower bids, reducing over-bidding, and hence yield smaller bid deviations. In addition to anticipated emotions, emotions may be integral, which arise due to the auction environment, accompanied by physiological changes prior to the auction (Teubner et al., 2015). Here, integral emotions have shown to be associated with lower bids when competing with human bidders. In the context of online shopping, emotions have shown to impact purchasing intentions and decisions, depending on whether positive or negative emotions were experienced (Pappas et al., 2014). Under the premises, we also expect to observe that context-specific emotional arousal, as measured by physiological changes, primarily drive the bidder's actions (i.e., the bids), in accordance with the framework for emotional bidding as shown in Adam et al. (2011).

While actions could be the culmination of a myriad of emotional processes, bids also could be the outcome of detailed strategic thinking and deliberative thought processes, involving cognitive effort and workload. In a survey-based Internet study on eBay participants, Möllenberg (2004) categorized bidders into two classes: "auctainers" and "smart bidders." Auctainers are experience-oriented, attracted by emotional stimuli, and tend to bid aggressively. In contrast, smart bidders are result-oriented, attracted primarily by cognitive stimuli and strictly adhere to preselected bidding limits. Such cognitive reasoning could be applied by the bidder due to several reasons and correspondingly bear different implications for bids. One of the primary tasks of the bidders in common value auctions, for instance, is to estimate the actual value of the item at stake. Assuming risk-neutral bidders, Kagel and Levin (1986) showed that in common value auctions the optimal bid is theoretically given by the difference between a bidder's own private signal and the commonly known error term with which private signals are drawn. Hence, determining the optimal bid typically involves the (1) interpretation of the private signal, (2) knowledge of the error term in drawing the private signal, (3) taking the difference between the two values, and (4) bidding at the right time (in the case of dynamic auctions). In addition to the above, Camerer et al. (2004) posited the cognitive hierarchy model, in which each player believes that he or she understands the game better than the other players. Such strategic thinking could involve computation of one's own strategy, as well as taking into account others' strategies, and iteratively, taking into account whether others account for others' strategy or not, and so on. The cognitive hierarchical model highlights the extent to which the information setting could determine the level of cognitive workload experienced in an auction. Given the informational setting of an auction,van den Bos et al. (2008) suggested that humans have limited cognitive abilities that make accounting for the winner's curse (Kagel and Levin, 1986) difficult, if not impossible. Hence, the process of estimating the value of an item itself, as well as finding the optimal bid to place, represent cognitively demanding tasks. So far, the direct underlying impact of the internal processes (emotional arousal, cognitive workload) on bid deviations has been established from previous work. We next outline how the relationships may be determined by aspects of the (external) auction environment, i.e., auction dynamics and value uncertainty.

4.2.2 The Role of Auction Dynamics

In the following, we outline how auction dynamics may impact the relation between emotional arousal, cognitive workload, and bid deviations. Considering static auctions, a single bid is submitted without knowledge of other bidders' actions or any degree of interaction, whereas dynamic auctions entail both elements. In English auctions, for instance, a bidder repeatedly experiences other bidders' actions and faces the decision whether to respond or not, enabling a potentially endless process and the possibility of "bidding wars" (Ariely et al., 2005) among subgroups of participants. Dutch auctions, as another example, involve an element of timing and a constant trade-off between delay, profit, and ri surrounding the item being contested for. While bidding is a complex task that can involve considerable amounts of computation, it was found to highly depend on the auction's dynamics. For instance, Katok and Kwasnica (2008) showed that at fast clock speeds, revenue in the Dutch auction was significantly lower than it was in the FPSB auction. Thus, even though the two auction formats (Dutch and FPSB auctions) are outcome-equivalent from a theoretical perspective, several differences exist in the overall outcome, indicating that besides economic considerations, other factors must be at play.

Ku et al. (2005) examined the influence of competitive arousal on bids for the case of live and Internet auctions, showing that the emotional aspect of "desire to win" is increased when rivalry and time pressure coincide, to mediate the effect of time pressure on bid deviations, resulting in over-bidding. Using a series of Dutch auctions with different clock speeds, Adam et al. (2012a) showed that in fast Dutch auctions bidders are more excited and stay longer in the bidding process as compared to slow Dutch auctions, thus resulting in lower prices in the former. Katok and Kwasnica (2008) suggested that auction dynamics determines whether and how emotional arousal impacts bids and hence outcomes. Using an experiment on risky decisions under time pressure, Slovic et al. (2007) demonstrated that the reliance on an affect heuristic seems to be exposed more clearly when the subjects' opportunity for analytic deliberation is reduced (e.g., due to time pressure), hence requiring an affective mode of judgement. The above studies indicate that high auction dynamics affect the extent to which emotional arousal impacts bid deviations, and hence the overall auction results. Considering situations of high dynamics, it is likely that the focus might be on "feeling" rather than "thinking" such that bids are rather guided by arousal than by cognition. In other words, it is likely that auction dynamics increase the impact of emotional arousal on bid deviations. Hypothesis H2.1 states:

Hypothesis 2.1: Auction dynamics (AD) moderate the relationship between arousal (AR) and bid deviations ($\triangle$B).

As just described, we expect the focus to shift towards emotional processes in high-dynamics situations and hence a less pronounced role of cognitive workload on bid deviations. A crucial determinant of the extent to which cognitive workload is likely to be applied in an auction environment is the amount of time available to deliberate. For illustration, consider a fight or flight scenario, e.g., when facing a dangerous situation. The dynamics here can be regarded as very high, i.e., considerations and actions need to take place in split seconds. In contexts of high time pressure, it has been shown, that consumers have a higher cognitive cost when there is less time available, due to increased information search and processing rates (Punj and Moore, 2009). Mann and Tan (1993) showed that time-pressured students generated fewer alternatives and considered fewer consequences in their decision-making process. It is hence possible that in situations of high time pressure, the cognitive process and consequently the cognitive workload, is higher. The situation of increased cognitive demand opens two possibilities: (1) that decisions are made using an affect-based heuristic, thus relying on automatic processes, rather than deliberative processes (Slovic et al., 2007), or (2) in the case that deliberative processes are applied, participants deviate more from optimal bid, since weighing all alternatives in the given decision context is a cognitively demanding task. Based on the research outline above, it seems plausible that the external factor of auction dynamics is a potential moderating factor on how cognitive workload impacts bid deviations. Hypothesis H2.2 states:

Hypothesis 2.2: Auction dynamics (AD) moderate the relationship between cog-

nitive workload (CW) and bid deviations ($\triangle$B).

4.2.3 The Role of Value Uncertainty

Another aspect specific to auctions is the level of uncertainty associated with the value of the underlying good. In common value auctions, for instance, the probability distribution of the item's value is the same for all bidders but its true value is unknown to the bidders at the time of the auction. Each bidder typically possesses information on the distribution from which the true value is drawn, by means of a more specific private signal (McAfee and McMillan, 1987). The private signal, however, entails some degree of uncertainty about the value of the good. As suggested by Yin (2006), value uncertainty may arise due to dispersed information across auction participants or the uncertainty about the trustworthiness of the seller. Both aspects were found to be significant drivers for bids and final prices. Some goods like oil drilling rights, for instance, are uncertain in nature, as prior exploration cannot fully and exactly ascertain what quantity of oil is likely to be extracted. Specifically, in common value auctions, assuming that each bidder receives a private signal about the common value, the value uncertainty for each bidder primarily stems from the variance with which the private signal is drawn. It is hence likely that people may bid past their initial limits since they use personal and social information to evaluate an item's value due to the uncertainty of information.

We first turn to the potential emotional ramifications of uncertainty for bid deviations. Eriksson and Sharma (2003) showed that different emotions (such as sadness and anxiety), have a different impact on the way uncertainty is perceived, subsequently impacting buyer-seller cooperation. Specifically, anxious individuals were found to be more likely to make decisions that reduced uncertainty and avoided risk. Loewenstein (2000) stated that fear tends to increase over time as a particular risk becomes temporally imminent, which produces the phenomenon of "chickening out," as the "moment of truth" draws near, and alters behavior. In the context of gambling, Cowley (2013) showed (1) that subjects underestimated the role of anxiety and overestimated the role of excitement when dealing with value uncertainty, and (2) that the inaccuracies in forecasting values occurred because the immediate emotional reactions to uncertainty are difficult to factor in. Thus, previous literature indicates that value uncertainty triggers internal emotional processes, and subsequently influences the course of decision. We hence postulate that facing higher degrees of value uncertainty might alter the influence of emotional arousal on bid deviations. Hypothesis H2.3 states:

Hypothesis 2.3: Value uncertainty (VU) moderates the relationship between arousal (AR) and bid deviations ($\triangle$B).

Next, we discuss the potential cognitive impact of uncertainty on bid deviations. Mousavi and Gigerenzer (2014) theorized that uncertainty is a context that requires knowledge, and cognitive deliberation, such that expert decisions under uncertainty are often compelled to rely on heuristic principles. In order to reduce uncertainty, people have been shown to resort to searching through memory for relevant knowledge or using cues from the task, hence signaling potentially a higher level of cognitive effort under uncertainty (Gilboa and Schmeidler, 2000). In auction-bidding processes, Muthitachareon et al. (2014) showed that consumers' goal of minimizing cognitive effort can explain the correlation between price premium and transaction uncertainty, thus highlighting that cognitive cost is a critical factor that drives decision-making processes. Under uncertainty, a trade-off has to be made between the costs of action (e.g., information search) and the risks in taking no action. For the case of FPSB common-value auctions,Kagel and Levin (1986) showed in experimental conditions, that higher value uncertainty led bidders to deviate more from optimal bid. Participants also had greater difficulties in estimating true values when uncertainty was high. Conjoining the empirical evidence from the literature, we suggest that value uncertainty in the auction environment determines how cognitive workload impacts bid deviations:

Hypothesis 2.4: Value uncertainty (VU) moderates the relationship between cognitive workload (CW) and bid deviations ($\triangle$B).

In the following, we outline the experimental auction setting to test the above hypotheses.

4.3 Materials and Methods

This section describes the experimental design of our study, including treatment and auction structure, and overall procedure. To test the hypotheses, we utilize a full-factorial within-subject experimental design with repeated trials. In our experiment, each participant takes part in a series of 40 auctions, where the treatment variables auction dynamics (AD: low or high) and value uncertainty (VU: low or high) are varied systematically. Hence, each of the four possible combinations occurs exactly ten times.

4.3.1 Auction and treatment structure

In order to test the above hypotheses, we utilize a full-factorial within-subject experimental design with repeated trials. The auction is designed based on Kagel's (1989) as well as Kagel and Levin's (2002) common value model. In each auction, the true value (Vo) is drawn randomly from the uniform distribution [15, 100], measured in monetary units (MU). Private information signals (x) are drawn randomly from the uniform distribution $[V_o - \epsilon, V_o + \epsilon]$, where ϵ represents the error term, or the value uncertainty in the private signal, i.e., how far away the private signal can be from the true value. In order to operationalize auction dynamics, participants played two auction formats (Dutch auctions, being a dynamic auction with limited time to submit bids, and FPSB auctions, being a static auction with no time pressure to submit bids). By varying the ϵ (and hence the interval) in which private signals are drawn, two levels of value uncertainty (3 MU and 12 MU) in information are presented. Bidders (computer and human) are provided their individually drawn private signal, while the error term and the distribution of the true value [15, 100] MU is common knowledge. Given x, ϵ, and the endpoint values, each bidder can hence compute an upper and lower bound on the value of Vo by considering min $(V_o + \epsilon, 100)$ and max $(V_o - \epsilon, 15)$. The expected bidding strategy is based on the RNNE strategy $(x - \epsilon)$ defined later in this work. Computer opponents are programmed to place the RNNE bid based on their respective randomly drawn private signals.

Each subject played against two computer opponents. Since humans have shown to behave differently in the presence of human vs. computer agents (Teubner et al., 2015), careful considerations were made with respect to the information levels that participants had. For instance, Grossklags and Schmidt (2006) show under a laboratory condition that common knowledge about the presence of software agents triggers more efficient market prices when the programmed strategy was employed. Furthermore, the authors interpret that the existence of a computer agent with an unknown strategy might boost curiosity and the willingness to participate in a potentially less favorable environment, due to the unspoken capabilities of a computer agent. Taking these results into account, in the current experimental design, we provided information to participants that they were bidding with two computer agents in each auction; however the exact bidding strategy of the agents was not revealed. In case of a tie, participants were informed that the winner was picked at random. The number of bidders is important information, since it leads participants to adjust their strategy based on the level of competition, and their wins and losses in the auctions. Since the primary focus in this study is on RNNE predictions, in order to control for a potential winner's curse we restrict this study to 3 bidders in each auction, analogous to Katok and Kwasnica (2008); Engelbrecht-Wiggans and Katok (2008); Astor et al. (2013) with 2 computer opponents for each human bidder.

In all auctions, participants could enter their bids in units of 0.5 MU, and could bid positive values only. As is characteristic of a FPSB auction, there was no limit on the time for participants to enter their bids. Whereas in the Dutch auction, a clock ticked downwards in units of 0.5 MU, at a speed of 0.5 seconds, modeling a dynamic auction and inducing time pressure (the speed of 0.5 seconds has been derived from previous experiments where participants could stop the clock at several speeds: (Adam et al., 2012b, 2015). Since the participants bid based on their private signal and error term information, indicating that the true value of the good is different in each round, they are subtly enforced to bid afresh in each round, avoiding the notion of ownership or a possible endowment effect.

4.3.2 Risk-neutral Nash Equilibrium in Common Value auctions

In this chapter, in order to assess the decision quality of bidders, the Risk-Neutral Nash Equilibrium (RNNE) as defined by Kagel (1989) has been adopted as the primary measure. In this section, we examine the derivation of this measure. The RNNE bid was defined based on the central assumption, that bidders are risk-neutral. In common value auctions, bidders are most likely to win if they have the highest estimation of the item's value (assuming that bids are an increasing function of these estimates). In other words, the winning bidder has the most optimistic, and hence highest estimate of the item's true value. If this problem of adverse selection is not accounted for in the process of defining a bidding strategy, winning bids are likely to result in negative profits Kagel and Levin (1986). This adverse selection problem in CV auctions is often referred to as the "winner's curse."

Most RNNE bid functions do account for the winner's curse in some way. Under the following assumptions:

1. the common value (x_0) of the auctioned item is randomly drawn from a known uniform distribution with upper and lower bounds $[\underline{x}, \overline{x})]$
2. each bidder is provided with a private information signal (x)

3. x is randomly drawn from a known uniform distribution with upper and lower bounds $[x_0 - \epsilon, x_0 + \epsilon]$
4. ϵ is common knowledge

then, the symmetric RNNE bid function $\gamma(x)$ for risk-neutral bidders is given by

$$\gamma(x) = x - \epsilon + h(x)$$

with

$$h(x) = \frac{2\epsilon}{n+1} exp[-\frac{n}{2\epsilon}(x - (\underline{x} + \epsilon))]$$

n stands for the number of bidders. Kagel and Levin (1986) provide detailed reasoning to incorporate the interplay of different strategic considerations into the "bid factor" $h(x)$, but as $h(x)$ approaches zero rather quickly as x moves beyond $(\underline{x} + \ epsilon)$, the RNNE bid function can be approximated by

$$\gamma(x) = x - \epsilon$$

In this chapter, subjects' behavior is assessed using this benchmark RNNE function. In addition, the two computer bidders are programmed with this bidding function, based on the private signal randomly drawn out to the computer bidders in each round. The above RNNE function fully accounts for the adverse selection problem mentioned earlier, but it does not account for risk aversion. Still, using the RNNE bid as a benchmark provides a convenient way to analyze the subjects' bidding behavior from a game-theoretic point of view.

4.3.3 Procedure

A total of 39 participants (28 male and 11 female bidders) were recruited for sessions of 90 minutes. We had to remove 2 participants from the dataset due to incomplete/ corrupted physiological measurements. Thus, we analyze a data sample of 39 - 2 = 37 participants (26 male and 11 female bidders). Participants were students, pursuing their

Bachelor or Master studies, from the domains of engineering, economic sciences, and information systems. To establish incentives and to create a link between bidding behavior and payoffs (Induced Value Theory, Smith (1976)), participants received a variable payoff based on all earnings or losses in the experiment, where 1 MU was converted to 0.05 EUR. Moreover, they received an additional fixed amount of 20 EUR. The payout structure was explained in the written instructions. Average payoff was 21.82 EUR. The study was conducted at (blinded for review), in compliance with the university's ethical guidelines, and following the recommendations for physiological measurements of the Society for Psychological Research (SPR). The experimental procedure is summarized in Figure 4.2. After arrival at the laboratory, the participants were welcomed, heart rate and EEG measurement equipment was set up in the participant's cabin. Electrocardiogram (ECG) sensors were attached first, followed by EEG electrode attachment, consuming roughly 10-12 minutes. The experiment instructions (including payoff rules) were distributed in written form to all participants and also read out aloud by our staff. Participants then answered a comprehension quiz with 6 questions to test their understanding of the instructions, followed by 2 trial rounds. After this, there was a 5 minute resting period, in which participants were asked to sit idle, which is used to record a baseline level for the physiological data.

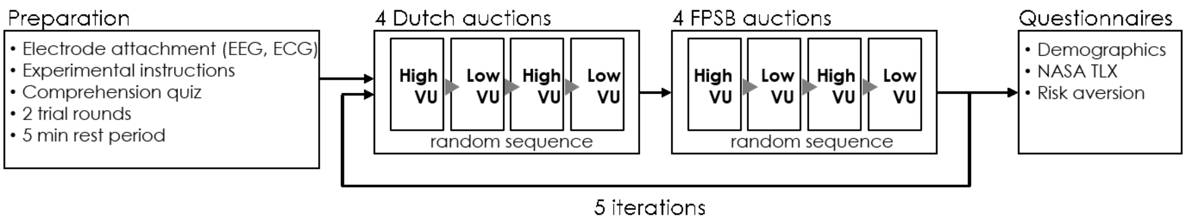


FIGURE 4.2: *Experimental Procedure*

In the main part of the experiment, each participant played 40 auctions (consuming about 40 to 45 minutes). As can be seen in Figure 4.2, the auctions were broken down into 5 iterations of 1 block of 4 FPSB and 1 block of 4 Dutch auctions, where in each block of 4 auctions, two auctions used the low VU, and two auctions used the high VU condition. This sequence within the blocks was determined randomly. Figure 4.3 shows the sequence of events E1-E6 during one auction process. The first event in each auction is the presentation of treatment information, and the private signal value (E1 in Figure 4.3). Based on the private signal, each participant either submitted a sealed bid in a FPSB auction, or engaged in a Dutch auction (E2). At the end of the bidding phase, three pieces of information were displayed in intervals of 5 seconds, one after the other: (1) the result: whether the participant won or not (E3) (2) the regret information: by displaying the bid of the highest bidder for lost auctions (E4). (3) the payoff information (E5): the profit/loss earned, taken as the difference between the winning bid and the true value in the current round. Then participants clicked on a "Next" button to proceed to the next auction (E6).

After the experiment, electrodes were detached (consuming 2 minutes), and participants were asked to take several questionnaires, including demographic data (gender, and age), the NASA TLX (Hart, 1988), and risk aversion (Holt and Laury, 2002) consumed roughly 12-15 minutes.

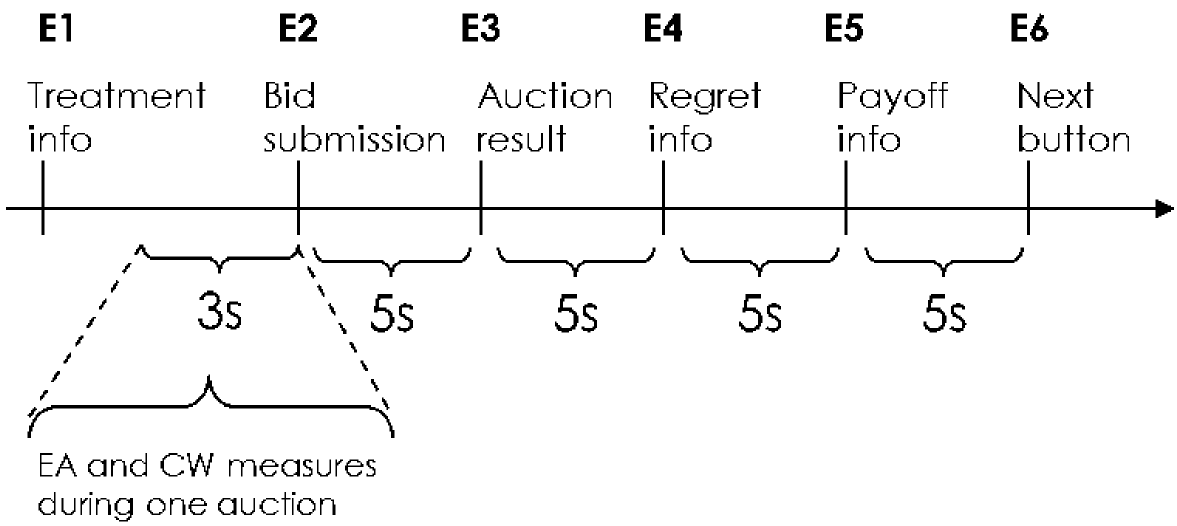


FIGURE 4.3: *Sequence of events E1-E6 and assessments of EA and CW during one auction process*

4.3.4 Measures

Table 4.1 summarizes the operationalization of the factors in the research model and the main statistic figures, as observed in the experiment. The trial rounds are not included in the analysis. First, to operationalize emotional arousal (EA), heart rates of all participants were measured before the experiment (baseline heart rate) and also before each bid. In order to make heart rates comparable across participants, we normalized the heart rates prior to the bid by dividing each value by a participant's baseline heart rate. EA of a bid was calculated by reducing the normalized heart rate values during the 3 to 1 seconds directly prior to the bid to a single factor using Principal Component Analysis. An EA value of 0 represents an average level of emotional arousal, whereas a value of 1 represents an arousal one standard deviation above average (across all participants and auctions). The process is described in greater detail in Appendix C, where we also depict participants' normalized heart rates for the different treatment conditions (Figure C.2).

Second, for cognitive workload (CW), we employed self-reported and physiological measures based on EEG data. The CW values used in our analyses are based on the EEG data. For the physiological measurement of cognitive workload, we adopted standard procedures (Ortiz de Guinea,Ana and Webster, Jane, 2013). The cognitive workload index for a bidder and auction was based on EEG data prior to event E2 (see Appendix C for a detailed description). As can be seen in Table 4.1, the CW values ranged from 0.03 to 1.18, where a value close to 0 corresponds to a "sleepy" state (low workload), and a value close to 1 represents high cognitive workload or "high engagement" (Charland et al., 2014). To measure perceived cognitive workload, the NASA TLX scale (Hart and Staveland, 1988) was employed. Appendix C depicts differences between perceived and measured cognitive workload (Figure C.1). Finally, based on their responses in the risk-aversion questionnaire by Holt and Laury (2002), participants were categorized into risk averse or not risk averse. In order to operationalize AD, we use an ordinal scale wherein 0 represents low AD (as FPSB auction) and 1 represents high AD (as Dutch auction). We operationalize VU also on an ordinal scale wherein 0 represents low VU ($\epsilon = 3$ MU) and 1 represents high VU ($\epsilon = 12$ MU). Bid Deviations (ΔB) We assess participants' bidding behavior in terms of deviations from the "optimal bid" (Kagel Levin, 1986). In particular, we define bid deviations (ΔB) on a ratio scale (in MU) by calculating the absolute difference between the actual bid and the optimal bid: ΔB = |Bid - Optimal Bid| (van den Bos et al., 2008). Kagel and Levin (1986) showed that the optimal bid can be well approximated by means of the Risk Neutral Nash Equilibrium (RNNE) bid function Y(x) = x - ϵ. The optimal bid is hence equal to the lowest possible true value of the underlying good, based on the observed private signal x and error term ϵ. It represents the bid that maximizes a bidders' expected payoff. The bid deviation can hence be written as follows: ΔB = |Bid - (x - ϵ)|. Due to the strategic equivalence of Dutch and FPSB auctions, the definition of the optimal bid, and thus for ΔB, holds for both types of auctions.

4.4 Results

We first consider the overall impact of our treatment variables auction dynamics and value uncertainty on bid deviations, i.e. (ΔB = (|Bid - Optimal Bid|) MU). The most striking result is that high value uncertainty yields much larger bid deviations than low uncertainty, for both conditions of auction dynamics (Figure 4.4). Moreover, high auction dynamics (Dutch), also yield generally larger bid deviations than low auction dynamics (FPSB). This

TABLE 4.1: *Summary of operationalization of the factors in the experiment*

Factor	Measure	Scale	Measurement statistics
Emotional Arousal (EA)	ECG-based emotional arousal index for each auction (Appendix A)	Numerical	M = –0.022 [SD = 0.98] min = –2.68, max = 5.67 median = –.11
Cognitive Workload (CW)	EEG-based cognitive workload index for each auction (Appendix A)	Numerical	M = 0.54 [SD = 0.10] min = 0.03, max = 1.18 median = 0.55
Perceived Cognitive Workload (PCW)	Weighted cognitive workload index for each participant on the NASA TLX questionnaire	Numerical	M = 4.91 [SD = 1.73] min = 1.00, max = 9.30 median = 4.60
Risk Aversion	Assessment of whether a participant is risk averse based on the risk aversion questionnaire (Holt & Laury, 2002)	Categorical	0: participant is not risk averse 1: participant is risk averse
Auction Dynamics (AD)	Auction format, with first-price sealed-bid auctions for low AD, and Dutch auctions with high AD.	Ordinal	0: FPSB auction, for low AD 1: Dutch auction, for high AD
Value Uncertainty (VU)	3 MU for low VU and 12 MU for high VU, uniformly distributed across the 40 auctions for a good whose true value ranged [15,100]	Ordinal	0: ϵ = 3 MU for low VU 1: ϵ = 12 MU for high VU
Bid Deviation (ΔB)	Absolute deviation from optimal bid ($\Delta B = \lvert Bid – Optimal Bid \rvert$)	Numerical (Monetary Units, MU)	M = 4.97 MU [SD = 5.69] min = 0 MU, max = 57 MU median = 2.50 MU

effect holds for both high and low value uncertainty. The impact of auction dynamics, however, is visibly less pronounced than that of value uncertainty. An ANOVA confirmed the relation to bid deviations statistically both for auctions dynamics ($F(1, 875) = 15.36$, $p<.001$) and value uncertainty ($F(1, 875) = 231.67$, $p<.001$).

Having established the base effects of auction dynamics and value uncertainty, we now consider the psycho-physiological measures emotional arousal (EA) and cognitive workload (CW). In a first step, we analyze these measures in in mixed-effects generalized least squares (GLS) regressions with random intercepts for participants. Auction dynamics is represented by a binary dummy variable, taking the value "1" for high dynamics (Dutch auction format) and "0" for low dynamics (FPSB). Likewise, value uncertainty is also represented by a binary dummy ("1" for high, "0" for low value uncertainty). Moreover, we include a dummy variable for risk aversion (Holt and Laury, 2002) and the variable Round, ranging from 1 to 40, controlling for a possible linear trend in bid deviations over the course of the experiment. As shown in Table 4.2, both factors EA ($b=-.149$, $SE=.157$) and CW ($b=1.953$, $SE=1.871$) do not significantly affect bid deviations. In line with our finding from above (on an aggregated level), high auction dynamics and high value uncertainty both yield larger bid deviations. Moreover, the coefficient for Round is also significant and negative, implying convergence towards the optimal bid, that is, learning among the participants. Risk aversion, in contrast, does not yield any significant effects. We discuss learning effects and findings on risk aversion in greater detail later on in this section.

We next examine, whether the impact of emotional arousal and cognitive workload on bid deviations depends on the auction environment, i.e., whether there occur interaction effects between the environmental and the psycho-physiological measures, as hypothesized in our research model.

4.4.1 The role of Auction Dynamics

We first consider the impact of emotional arousal and cognitive workload on bid deviations, depending on the different auction dynamics conditions (high/Dutch or low/FPSB). For the analysis, we extend the regression models from above, including the respective interaction terms. We consider the physiological measures at the moment prior to placing the bid (corresponding to E2 in Figure 4.3). The results of the respective GLS regressions are summarized in Table 4.2. For the low AD/low VU baseline, Regression I reveals that higher emotional arousal leads to significantly smaller bid deviations. One unit of

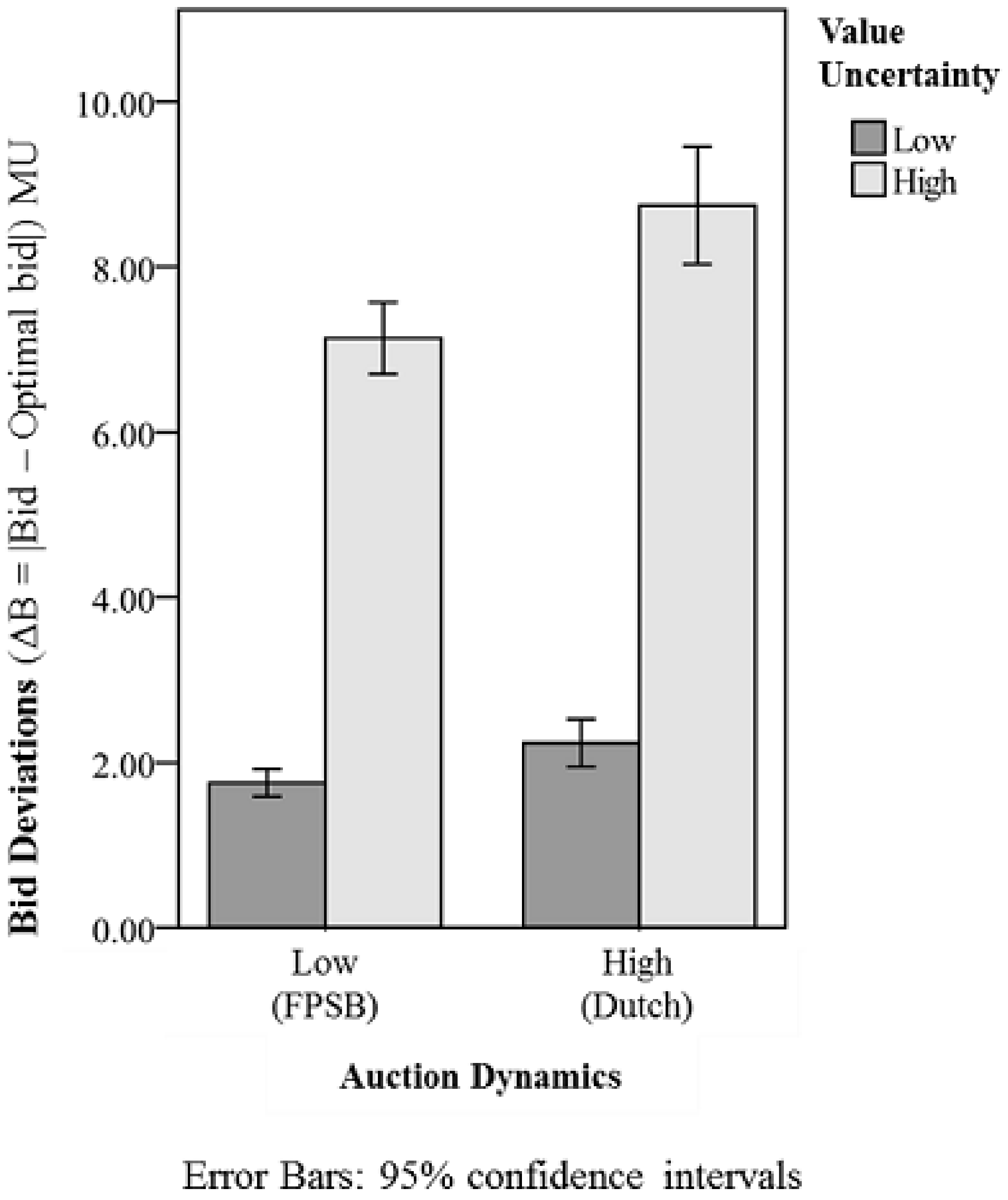


FIGURE 4.4: *Mean Deviations from RNNE in MU*

emotional arousal decreases deviations by .468 MU (SE=.227, $p<.05$). High AD significantly increase deviations for average levels of emotional arousal, i.e., at EA=0 (b=.779, SE=.341, $p<.05$).

Importantly, emotional arousal in the presence of high auction dynamics, i.e. in Dutch auctions, also increases deviations. The coefficient here is .635 (SE=.339, p<.05), which overcompensates the effect of EA in FPSB auctions and hence transforms the mitigating effect of EA into an aggravating one (.635 + (-.468) > 0). Our data hence supports H2.1, i.e., that auction dynamics moderate the role of emotional arousal on deviations, such that high auction dynamics increase the impact of emotional arousal on bid deviations. Second, Regression II depicts the impact of cognitive workload on bid deviations and how high auction dynamics alter its impact. Here, we neither find a significant base effect of cognitive workload on deviations, nor do high auction dynamics change the picture. H2.2 is hence not supported.

Figure 4.5 depicts the differences in the component spectral plots, for the 16 channels considered in the Independent Component Analysis stage, for Dutch and FPSB auctions for one subject. Components with eye artifacts, have already been removed. By eyeball inspection, the epicenter of spectral activity is different for channels 6, 8, 11, 12, 14 and 16, between the two treatments. For this particular subject, in Dutch auctions, spectral activity is weaker in the frontal area (except channel 12) than in FPSB auctions. In the remaining channels, there are no significant differences between the two treatments.

4.4.2 The role of Value Uncertainty

We now turn to the impact of emotional arousal and cognitive workload on bid deviations, depending on the conditions of value uncertainty (low or high), again based on Regressions I and II. First - for low AD and low VU as already noted above - higher emotional arousal leads to significantly smaller bid deviations. High VU significantly increases deviations at EA=0 (b=5.284, SE=.275, p<.001). In the high VU condition, the impact of EA on bid deviations is not significantly altered (b=.364, SE=.282). Hence, even though the general level of bid deviations is markedly higher in the high VU condition, it does not moderate the impact of EA on bid deviations. H2.3 is thus not supported by our data.

Moving on to the moderating role of value uncertainty on the impact of cognitive workload on bid deviations (H2.4), Regression II shows that under high VU, there occurs significant additional impact of CW on deviations. One unit of cognitive workload (which reflects the transition from its lowest to its highest observed values), here increases bid deviations by 6.331 MU (SE=2.654, p<.05), whereas the effect is insignificant for low

TABLE 4.2: *Impact of Arousal and Cognitive Workload on deviations from RNNE strategy*

	Dependent Variable: **ΔB =** |Bid – Optimal Bid| MU	
	b (SE)	*b* (SE)
Emotional Arousal (EA)	–.149 (.157)	
Cognitive Workload (CW)		1.953 (1.871)
Dummy: Auction Dynamics (AD)	.790* (.341)	.792* (.341)
Dummy: Value Uncertainty (VU)	5.255*** (.275)	5.266*** (.276)
Dummy: Risk Averse	.659 (1.274)	.803 (1.232)
Round (#1—40)	–.027* (.012)	–.024* (.012)
Constant	1. 855*** (1.215)	.606 (1.646)
R^2 within (R^2 overall)	.315 (.220)	.314 (.228)

N=878, Number of subjects = 37. 2 subjects were removed due to incomplete data points. Number of possible cases = 20(FPSB)* 37 (subjects) + 20 (Dutch) * 37 (subjects)* (1/3) = 986, since participants are expected to win 1/3rd of the auction cases. In the case of Dutch auctions, only auctions where participants clicked (and lost by a small margin) were available. Auctions where participants did not click (and hence lost) were not considered in the computation of bid deviations. Both regressions are based on GLS regressions with subject random effects. Regression coefficients (*b*) with standard errors (*SE*) in parentheses. + *p*<.1; * *p*<.05; ** *p*<.01; *** *p*<.001

TABLE 4.3: *Moderating influence of auction dynamics and value uncertainty on bid deviations*

	Dependent Variable: Δ**B =** |Bid – Optimal Bid| MU	
	H1a, H2a (Regression I)	H1b, H2b (Regression II)
	b (SE)	*b* (SE)
Emotional Arousal (EA)	–.468* (.227)	
Cognitive Workload (CW)		–1.828 (2.358)
Dummy: High AD	.779* (.341)	–1.076 (2.020)
Dummy: High VU	5.284*** (.275)	1.847 (1.455)
EA × High AD	.635* (.339)	
EA × High VU	.364 (.282)	
CW × High AD		3.515 (3.791)
CW × High VU		6.331* (2.654)
Dummy: Risk averse	.657 (1.267)	.737 (1.262)
Round (#1—40)	–.028* (.012)	–.023* (.012)
Constant	1.852 (1.209)	2.712 (1.845)
R^2 within (R^2 overall)	.318 (.227)	.319 (.234)

N=878, Number of subjects = 37, 2 subjects were removed due to incomplete data points. Number of possible cases = 20(FPSB)* 37 (subjects) + 20 (Dutch) * 37 (subjects)* (1/3) = 986, since participants are expected to win 1/3rd of the auction cases. In the case of Dutch auctions, only auctions where participants clicked (and lost by a small margin) were available. Auctions where participants did not click (and hence lost) were not considered in the computation of bid deviations. Both regressions are based on GLS regressions with subject random effects. Regression coefficients (*b*) with standard errors (*SE*) in parentheses. + *p*<.1; * *p*<.05; ** *p*<.01; *** *p*<.001

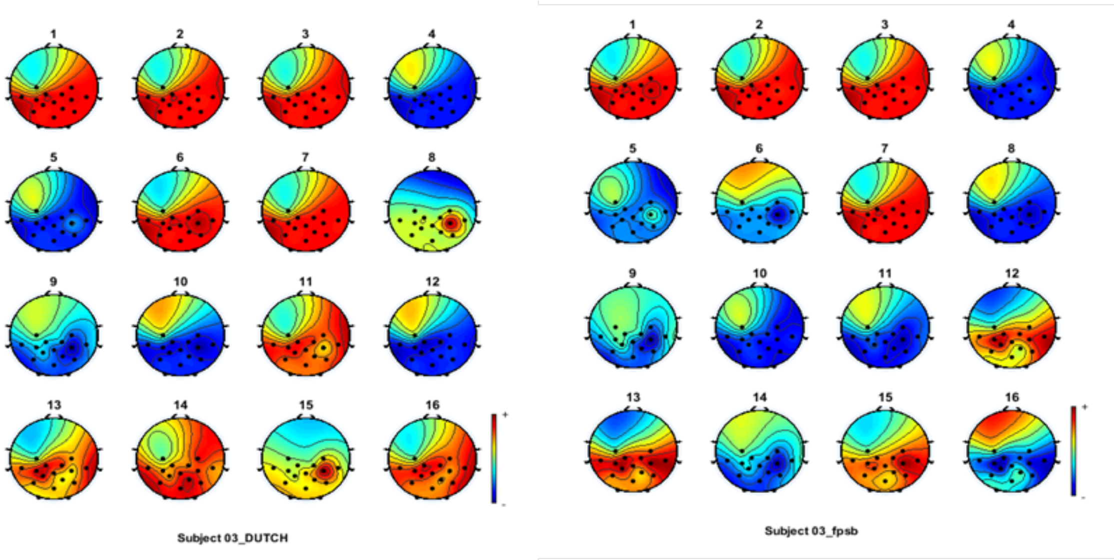


FIGURE 4.5: *Component spectral maps of 16 channel data, for one subject, for Dutch (left) and FPSB auctions (right)*

VU (b=-1.828, SE=2.358). Our data hence supports hypothesis H2.4, i.e., that value uncertainty moderates the role of cognitive workload on bid deviations, where high value uncertainty increases the impact of CW on bid deviations. Interestingly, when considering cognitive workload, the treatment variables themselves do not have a significant main effect (Regression II, Table 4.3), possibly explained by high variance in the EEG data, as reflected in the standard errors of the regression. To provide a more complete picture, we conducted additional 3-way-interaction regressions including VU, AD, EA, CW, and the respective interaction terms as independent variables in Appendix C (Table C.1), the results of which are consistent with the above findings.

Figure 4.6 depicts the differences in the component spectral plots, for the 16 channels considered in the Independent Component Analysis stage, for low and high value uncertainty treatments, for one subject. Again, components with eye artifacts, have already been removed. By eyeball inspection, it can be observed that the epicenter of spectral activity is different for channels 3, 4, 5, 6, 7, 10, 11, 13, 14, 15, 16. For auctions with high uncertainty, spectral activity is overall more pronounced (indicated by spectral acitvity in red, for channels 4, 5, 6, 7, 10, 16) than in low uncertainty, although not necessarily concentrated in the frontal area. In the remaining channels, there are no significant visible differences between the two treatments.

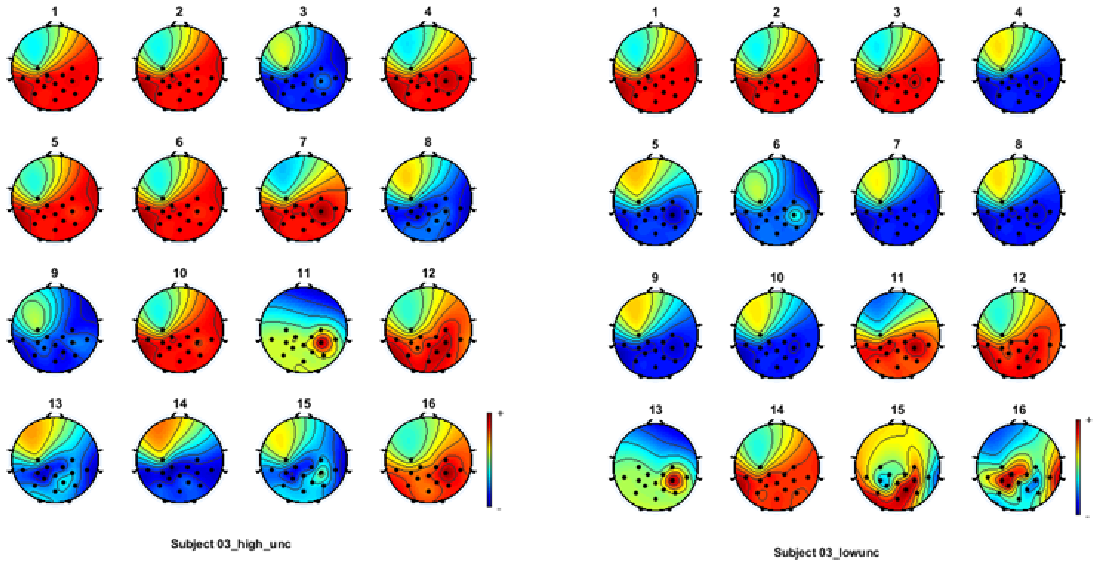


FIGURE 4.6: *Component spectral maps of 16 channel data, for one subject, aggregated for auctions with high (left) and low (right) value uncertainty*

4.4.3 Risk Aversion and Learning Effects

We now turn towards risk aversion and learning effects. For independent private value models, higher individual risk propensity can only be reflected in lower bids (larger outcome variance). In contrast, common value models yield risk both for lower (chance for particular high profits/ risk of not winning the auction), and higher bids (chance of winning the auction/ risk of experiencing the Winner's Curse). In fact, as can be seen in the regressions in Table 4.2 and Table 4.3, controlling for risk aversion does not yield any significant impacts on bid deviations. In line with Kagel and Levin (1986), the result suggests that, for common value auctions, risk aversion does not generally push bids in one or the other direction.

To examine and control for learning effects during the experiment, we included the auction number (Round) as an independent variable into the regression. The results in Tables 2 and 3 show that participants deviated less over the course of the experiment (all coefficients between -.023 and -.028; all p-values below .05). The effect could be explained by learning effects that might occur as participants learned from the auction outcomes over time. Hence, bidders potentially adapted their bids to avoid losses due to over or underbidding. The observation is in line with previous literature (Clemons and Weber, 1996). However, comparing the standardized coefficients of the interaction effects between EA and AD (5.302) and between CW and VU (7.280) with that of learning (-1.12, -.96 respectively), it can be seen that the impact of the auction environment in determining the extent to which internal processes increase deviations, is stronger than the mitigating impact of learning. We hence suggest that the hypothesized interaction effects were not affected by learning. A possible explanation is that the interval from which the private value signals were drawn was large, i.e., [15, 100], such that participants had to newly assess the situation in every round. The diminished learning effect is in line with Kagel and Dyer (1988), who described learning in a similar common value setting as a "trial and error learning process, which results in stable response functions that are not 'best replies', and in which agents fail to 'understand' the underlying economic process, so that changes in economic conditions result in sharp disruptions to the market, and the learning process must repeat itself" (p. 184).

4.5 Discussion

4.5.1 Summary of Results and Theoretical Implications

Electronic markets and auctions in particular offer a perfect stage for the dynamic interplay of cognitive and affective processes. In the present study, we quantified cognitive workload and emotional arousal by means of physiological measurements and examined how specific (external) properties of the auction environment, i.e., auction dynamics and value uncertainty, affect the impact of EA and CW on the bidders' deviations from optimal bids. We showed that the (external) auction environment is important for understanding the impact of internal processes (cognitive and affective) on bidding behavior. First, the environmental factors auction dynamics and value uncertainty moderated the effects of different internal processes on bid deviations. While auction dynamics moderated the impact of emotional arousal (supporting H2.1), value uncertainty moderated that of cognitive workload (supporting H2.4). Second, the moderations were mutually exclusive - i.e., auction dynamics did not moderate the impact of cognitive workload on bid deviations, and value uncertainty not that of emotional arousal (H2.2 and H2.3 not supported). Third, both higher AD and higher VU increased the impact of their respective affective/ cognitive processes on bid deviations.

With respect to auction dynamics, we argue that participants are likely to be at ease in a FPSB auction as the auction environment does not distort their emotional state, and hence are more likely to bid close to the optimal bid. The elements of excitement and suspense in Dutch auctions may provide hedonic value but also lead to larger bid deviations and hence lower overall individual payoffs (Adam et al., 2012a). Moreover, high auction dynamics increased bidders' reliance on emotional processes, while the role of cognition remained unchanged. The picture was different for value uncertainty, however. High value uncertainty, i.e., a potentially more challenging estimation process for the underlying good's true value, seemed to be associated with more pronounced processes of reflection, generating a higher cognitive demand, and consequently increased bid deviations.

It is important to highlight that we pursue a moderation model to ascertain to what extent environmental factors alter the relationship between internal processes and bid deviations. A moderator variable is one that influences the strength of a relationship between two other variables (Baron and Kenny, 1986). In contrast, a mediator variable is one that explains the relationship between the two other variables. In our study, a mediation model could be employed to examine whether the intensities of internal processes mediate the direct impact of the auction environment on bid deviations. However, a mediation analysis (Table 4.4) neither revealed significant indirect effects for emotional arousal nor for cognitive workload. Hence, from a theoretical perspective, it cannot be stated that the direct impact of auction dynamics and value uncertainty can be explained via the path of different intensities in emotional arousal or cognitive workload. Rather, the nature of the decision process changes with the auction environment, as the strength of the relationship between bid deviations and internal processes changes.

4.5.2 Managerial Implications

While theoretically bidding behavior is determined as the result of a bidder's internal processes (cognitive and/or affective), it is difficult if not impossible to disentangle how exactly internal processes lead to a decision. In fact, auctioneers in practice might choose to abstract from or even completely ignore bidders' underlying internal processes and focus solely on the ultimate impact of environmental conditions on bid deviations. Final prices are certainly one primary concern of practitioners, however, an understanding how the external auction environment affects the impact of internal processes' on bid deviations also has several important managerial implications. First, understanding the importance of cognitive and affective processes on bid deviations in a particular auction environment can be useful for training purposes and de-biasing bidders. For instance, in contexts of time pressure, bidders' emotion regulation capabilities could be trained by providing live biofeedback (Astor et al., 2013b). In contexts of value uncertainty, participants could be trained to maintain their cognitive workload at an optimal level, in order to achieve better outcomes. Second, practical auction design builds on theoretical models of bidding behavior, which are based on assumptions on bidders' cognitive reasoning and emotional arousal levels. Understanding the scenarios in which the importance of one or the other internal process becomes more pronounced might be essential to challenge assumptions and to test the robustness of existing theories in different types of auctions.

Electronic auctions are increasingly relevant for a wide range of industries. In the context of retailing, several e-commerce platforms realize a high percentage of their total revenues through electronic auctions (e.g. DealDash, MadBid, 1-2-3.tv, and eBay). In addition to e-commerce, auctions have proven to be particularly useful for emergency situations in health care (Smits and Janssen, 2008) or in crisis response management, where immediate and dynamic re-allocations are necessary to respond to the situations in a timely manner (Airy et al., 2009). Understanding the influences of external environment on human bidding would hence be useful in designing robust systems that proactively factor in the relationship between internal processes and bid deviations. In the context of spectrum auctions, Goeree and Offerman (2003) write that the auctions used to allocate spectrum licenses represent examples of high common value uncertainty, and Kroemer et al. (2016) show that bidders deviate significantly from optimal bids in the clock phase of spectrum auctions. In our study, high value uncertainty impacts how cognitive workload affects bid deviations. Hence, de-biasing in high uncertainty conditions should focus on cognitive rather than affective aspects of decision making. Secondly, auction format determines

TABLE 4.4: *Mediation analysis: Do emotional arousal and cognitive workload mediate the influence of auction dynamics and value uncertainty on bid deviations.*

	Dependent Variable ← Independent Variable	**Dependent Variable:** ΔB = (|Bid – Optimal bid|) MU		
		Direct effects	Indirect Effects	Total Effects
Mediation Test 1: Arousal mediates impact of AD on bid deviations (ΔB)	EA ← AD	.143 (.079)$^{+}$		
	ΔB ← EA	.291 (.194)		
	ΔB ← AD	1.755 (.455)***	.041(.036)	1.797(.454) ***
Mediation Test 2: Cognitive workload mediates impact of AD on bid deviations (ΔB)	CW ← AD	–.019(.008)*		
	ΔB ← CW	4.224(1.816)*		
	ΔB ← AD	1.881(.454)***	–.083(.050)$^{+}$	1.797(.454) ***
Mediation Test 3: Arousal mediates impact of VU on bid deviations (ΔB)	EA ← VU	–.025(.066)		
	ΔB ← EA	.371(.173)*		
	ΔB ← VU	5.220(.341)***	–.009(.024)	5.210(.341) ***
Mediation Test 4: Cognitive workload mediates impact of VU on bid deviations (ΔB)	CW ← VU	–.005(.007)		
	ΔB ← CW	4.285(1.623)**		
	ΔB ← VU	5.234(.341)***	–.023(.031)	5.210(.341) ***

N=878, Number of subjects = 37. + p<.1; * p<.05; ** p<.01; *** p<.001

how bidders' emotional arousal impacts bidding. Hence, when aiming to minimize deviations from the optimal bid, we recommend applying an auction format which results in a smaller influence of auction dynamics on bid deviations, as well as considering appropriate de-biasing techniques (such as emotion regulation).

Overall, auction mechanisms should take the internal state of bidders into account, e.g., by designing adaptive systems (Feigh et al., 2012) that aid bidders to reduce deviations from the optimal bid, drawing on emotion detection methods from physiological responses (Hariharan and Adam, 2015). With respect to dynamics, the design element of time pressure should be administered with caution. One alternative would be to adopt the design of slow Dutch auctions (e.g., 5 seconds instead of the 0.5 seconds per unit decrease), wherein bidders' heart rate was found to be significantly lower (Adam et al., 2012a). However, it is important to note that the emotional arousal instigated through auction dynamics can be also be source of hedonic value for the bidders, particularly in the domain of Internet consumer auctions (Adam et al., 2015). Hence, auctioneers might deliberately decide to increase auction dynamics to induce excitement on the platform despite ramification in terms of larger bid deviations.

4.5.3 Limitations and Directions for Future Research

The present study has limitations which shall be discussed here. First, the optimal bid function assumes bidders to be risk-neutral, while in fact risk propensity varies across the population and most people tend to be slightly risk averse (Holt and Laury, 2002). Kagel (1989) predicted that, assuming FPSB auctions and a common value model, risk-averse bidders would bid lower than the RNNE, and risk-affine bidders higher. To control for such potential effects of individual risk aversion, we included a control variable in our regression models, assessed using the Holt and Laury (2002) test. Individual risk aversion, however, did not significantly affect bid deviations. How risk aversion (possibly) varies over the course of the experiment and interplays with value uncertainty, auction dynamics, emotional arousal, and cognitive workload needs further evaluation.

Second, other personality characteristics may impact how emotional arousal and cognitive workload affect behavior. For instance, emotion regulation strategies have shown to impact the emotion levels experienced and also to affect decision-making (Gross and John, 2003). Similarly, time pressure might be perceived differently depending on how a participant appraises the situation (e.g., stress vs. positive challenge). For cognitive workload, individual differences in cognitive needs and abilities should also be taken into account (Cacioppo and Petty, 1982). Such personality traits are likely to affect the interplay of the EA, CW, and auction bidding. They are, however, beyond the scope of this work. Turning to demographic factors, we did not consider physiological and behavioral variance due to gender, age, or experiment/auction experience. In particular, gender effects have been mentioned in several earlier auction studies (Ham and Kagel, 2006; Casari et al., 2005). However, owing to the small sample size of our study, it was neither possible to uncover systematic gender effects, nor possible to interpret the lack of significance with regard to bid deviations. These factors hence warrant further research.

Third, in this experiment, participants interacted with computer bidders only. Many auctions in e-commerce and competitive tendering procedures, however, are held among humans. Recent research showed that affective processes are stronger when bidders interact with human opponents as opposed to human-computer interaction

In the current study, we have taken efforts to combine the two schools of thought, namely the cognitive and the affective world in the context of auction bidding. To the best of our knowledge, there exist to date no studies that have systematically investigated the relationship between these factors at specific auction events (immediately prior to placing a bid) using physiological measurements. The distinct role of affective processes on bid deviations was evident for different levels of auction dynamics, whereas cognitive workload affected bid deviations only in the presence of high value uncertainty. However, the mentioned considerations are limited to only two aspects of the auction environment. Further potentially important levers include other auction formats (English, Vickrey, or Japanese), time pressure, and different levels of information granularity. Moreover, the presented results should be contrasted against results obtained when using independent private value (IPV), instead of common value (CV) models. Finally, a common explanation for bid deviations is that bidders fail to adequately take into account that the winning bidder is likely to have overestimated the true value of the good, that is, the winner's curse (Kagel and Levin, 1986; Casari et al., 2005). With as few as three or four bidders per auction, Kagel and Levin (1986) showed that the winner's curse was less pronounced and bid deviations were smaller than for larger numbers of bidders. Hence, future work should extend our experimental design to higher numbers of bidders per auction.

4.6 Conclusion

Turning to the research question RQ2 posed in the beginning of this chapter, it can be seen that, in a group context of auction, the external influences of auction dynamics and value uncertainty indeed moderate the role of integral arousal and cognitive workload (respectively) on RNNE bidding behavior. Specifically, the significant role of auction dynamics, in moderating the role of emotional arousal on bidding behavior, has been observed in this study. Secondly, value uncertainty was shown to moderate the role of cognitive workload on bidding behavior. Hence, we argue that understanding the influence of external influences on bidding behavior, is improved by understanding the underlying affective and cognitive processes that they impact. Both the cognitive and affective processes have a significant role on bididng behavior, and need to be considered together in constructing behavioral models. Auction design needs to consider changes in the impact of bidders' internal states on bidding behavior based on changes in the auction environment. Decisions based on affective processes may provide a heuristic where there is insufficient time for deliberation and reasoning. Real-time methods such as proposed by Fernández et al. (2013), (Visser and Parasuraman, 2011), and Astor et al. (2013b) could be used to provide neuro-adaptive interfaces and biofeedback, which in turn may help to support bidders to bid closer to the optimal bid. While we have not conducted the study where subjects bid with other human subjects, but rather interacted with computer bidders, we believe that the results may be observable in a human-human group setting as well, and this will have to be verified in future work. In the next chapter, we look at the the influence of integral arousal and cognitive workload in a context with the presence of other human decision-makers, namely a serious game in cooperative and competitive modes.

Chapter 5

Factors for performance differences in interactive serious games

> “Competition has been shown to be useful up to a certain point and no further, but cooperation, which is the thing we must strive for today, begins where competition leaves off.
>
> FRANKLIN D. ROOSEVELT

5.1 Introduction

As stated in the epigraph, competition and cooperation, are two powerful influences, on how we bind together socially, and how this in turn makes up group behavior. Whether we behave in the same way when acting as an individual, as we function in a group, is a pertinent and relevant question to address, specially in the context of group decision-making. For instance, deciding whether it is profitable to cooperate or not, is often a non-trivial decision process, specially when the extent to which we involve ourselves is at stake. A common example for this, would be the case of the public goods problem, where people have to decide how much to commonly contribute to a common pool, which may be viewed upon as an act of cooperation and sharing. As stated in the epigraph, in the larger sense of the society, competition has shown to have its limitations, despite its immediately attractive elements, such as the gratification of winning. The case of cooperation is hence argued, which is essential in order to achieve larger objectives not fulfilled by competition - such as stability, or maximizing economic welfare.

Cooperative and competitive processes are also important to understand, in the context of using information systems. Due to several reasons, using ICT for collaboration (or to foster competition, for instance, by ranking methods), might be favorable to traditional face-to-face methods. Using information tools might enable subtle and abstract representations of the contexts. It improves communication, by decreasing the need for explicit communication, but rather relying on implicit communication. It might also aid in receiving live updates about others' activities, or performance levels, which is often difficult to achieve in a traditional face-to-face method. While these are definitely advantageous from an organizational perspective (Te'eni, 2001), it is unknown, whether such information systems actually aid people, to perform better specially in cooperative and competitive situations. To this end, in this chapter, we focus upon a specific case, where cooperation and competitive modes are easy to elicit, with a readily available performance measure, namely, serious games. In the context of serious games, we study the influence of various factors, which might explain performance in the two modes of interaction.

Online collaboration and serious games are becoming increasingly common in both work and private environments (McGonigal, 2011). Serious games are digital games that are used for purposes other than pure entertainment (Susi et al., 2007). They usually have a specific goal, such as education, training, or creating awareness on social issues. By using a casual game to involve ordinary web users, Phylo, a human-based computing framework applied "crowd sourcing" techniques to solve the computationally unsolvable Multiple Sequence Alignment (MSA) problem (Kawrykow et al., 2012) using pattern recognition skills of the crowd. Games such as StrikeCom (Twitchell et al., 2005), are being designed to create group communication and interaction in multiple communication modes, for instance, to teach warfare techniques to battle commanders. Other games enable participants with widely varying backgrounds, motivations, and personal agendas to effectively and efficiently address complex problems, such as climate change (DeFrank and Hillyer, 2013; McGoff et al., 1990).

The application of (serious) games to work environments has intensified interest in theoretical and empirical research on what has been termed as the "multidimensional and multilayered construct" of gameplay (Poels et al., 2007). In this paper, we seek to understand, to what extent elements of game design explain individual and group game performance. By understanding these determinants of game performance better, we extend these results to an organizational context, where designing games to help employees increase their performance as well as feel comfortable is gaining interest (Mollick and Rothbard, 2013; Reeves and Read, 2013).

To exploring performance differences between individuals, a number of factors have been identified as relevant in literature. These are broadly characterized as being contextual and personality-related (LePine and van Dyne, 2001; Mischel and Shoda, 1995). Contextual factors - which describe features of the individual's environment - focuses on rules, tasks and rewards (Richardson et al., 2012), and changes in these parameters have shown to enhance performance. On the other hand, personality-related factors generally fall into two categories. The first is concerned with stable characteristics, leading to idiosyncratic behavior across many contexts and for a reasonably long period of time, such as personality traits (Feldmann et al., 2014), need for cognition (Cacioppo and Petty, 1982) or emotion regulation skills (Gross and John, 2003). The other category comprises of dynamic processes that vary widely within an individual, between contexts and in comparatively short time intervals, such as emotions (Astor et al., 2013) or attention, and cognitive workload (Li et al., 2014).

To this end, the overarching research question we explore in this chapter, is as follows:

RQ3: In a social context, how do external influences (cooperative and competitive game playing mode), and personality-related factors (characteristics and internal processes) impact individual and group game performance?

The fact that contextual and personality-related features are highly interrelated makes explaining and predicting individual (as well as group) performance a challenging research task (Farh et al., 2012). In this paper, we orient ourselves to the cognitive-affective personality system by (Mischel and Shoda, 1995), to examine the interrelationships between (1) two contextual factors: social interaction settings and gender formation, (2) stable characteristics: namely emotion regulation, and need for cognition, and (3) dynamic internal processes: namely emotions and cognitive workload; on individual and group game performance.

To this end, we conducted a laboratory experiment in which participants played a pattern recognition game in two modes - cooperative and competitive - and measured the above factors in questionnaires. First, we find that game performance depended on contextual setting: participants performed better in cooperative than in competitive mode, and male participants performed better than females. Second, personality-related factors partially explained this difference. Of the stable characteristics: engaging in emotion reappraisal led to a better performance across game playing modes. Analyses on the group level showed that some personality-related factors (such as need for cognition) - while largely irrelevant on the individual level - played a large role in determining group performance. Third, dynamic processes of emotion significantly predicted game performance, whereas the process of cognitive workload was not equally significant. This result highlights that emotional (and experiential) influences impact game performance more readily, than cognitive processes.

This chapter is structured as follows. First, we provide theoretical background and relevant literature on factors that drive performance differences in games. Second, we outline the experiment design, the procedure in collecting the data, and describe the measures employed. Third, we present the results, discuss their implications, and propose possible directions for future research.

5.2 Theoretical Background

We consider the question of human behavior in serious games from an "interactionist" point of view (Zhao, 2005) - i.e., to explain human behavior by what is known as triadic interactions between person, environment, and behavior (Lewin, 2013; Bandura, 1986; Mischel and Shoda, 1999; Funder, 2006). To encompass these triadic interactions, Mischel and Shoda (1995) provide a framework: the cognitive-affective personality system (CAPS). The components of the CAPS framework have been enlisted as encodings, expectancies and beliefs, affects, goals and values, competencies and regulation skills. First, humans encode features of the environment (i.e. mentally classifying or representing the self, other people, and events). These encodings then interact with the other components of CAPS to generate a pattern of inhibition and activation (e.g., encoding a situation as "physical danger" and encoding the self as "self-defense expert" may give rise to expectancies of attaining the goal of "surviving unharmed" successfully and serve to increase confidence and efficacy beliefs). The result of the encoding process and the subsequent interactions between the cognitive-affective components is then manifested as a specific behavior (Mischel and Shoda, 1995).

The CAPS model has been applied in the IS domain, in order to model organizational communication and to design appropriate IT communication systems (Te'eni, 2001). We apply the CAPS model to the domain of serious games as a means of developing appropriate gaming environments for purposes other than entertainment (e.g., training, education, or work collaboration).

Several taxonomies have been proposed in literature that encompasses the different kinds of psychologically relevant features, in situations and situation characteristics (Rauthmann et al., 2014; van Heck, 1984). We focus open two factors, which have proven to be highly deterministic of game performance, and are also applicable to organizational contexts. The first contextual factor of serious games we consider is the social interaction setting - whether the game mode is one of competition or cooperation. The second one we consider is that of gender: whether female players differ significantly from male players. With these contexts, we attempt to shed light on how certain dispositional variables (i.e., personality factors) interact with these contextual factors to activate cognitive-affective personality processes and which behaviors will result from these interactions

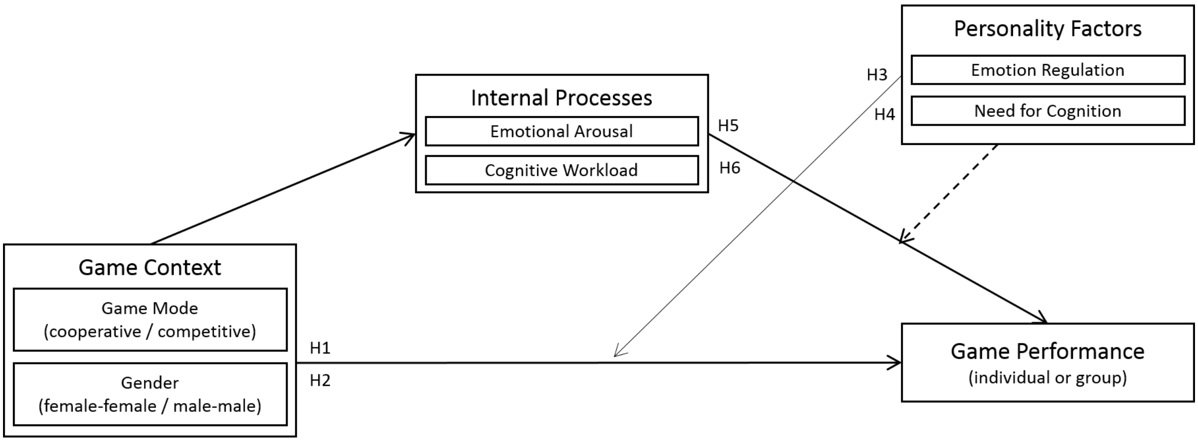


FIGURE 5.1: *Research Model*

5.2.1 Game context and Game Performance

Game playing modes may be broadly classified as (i) individualistic: where one's actions have no effect on others, (ii) cooperative: where individual actions promote the goals of others, (iii) competitive: where individual actions obstruct others' actions, and (iv) cooperative-competitive: e.g., multiplayer games in which players compete with each other as groups (Liu et al., 2013).

In the context of cooperative games and player motivation, the bounded generalized reciprocity behavior - which proposes that people will behave positively toward those who are expected to reciprocate such behaviors, thus effectively protecting and furthering one's self-interest - could be the underlying theory behind cooperative behavior (Velez, 2015). In accordance with this, it has been shown that playing with a helpful teammate increased the tendency of in-group members to reciprocate pro-social behaviors, as well as led to increases in pro-social behaviors between teammates (Velez, 2015). Also, the fundamental aspects of cooperation (such as an environment that fosters welfare, and makes game play more interesting) could be a performance driver by itself (Liu et al., 2013). A cooperative goal structure was found to lead to greater effort put into the game than a competitive goal structure (Peng and Hsieh, 2012). Even merely referring to the average social payoff has shown to foster game performance, and promote cooperation in a simulation-based spatial prisoner dilemma's games (Shigaki et al., 2012). In summary, prior research suggests that cooperative game elements buoy up game motivation and performance.

Turning to the other social mode of interaction in games, competition has shown to influence the degree of user engagement in the game, as well as impact the motivation to expend effort (Peng and Hsieh, 2012). For instance, in first person shooter games, it was shown that competitive interaction motives were the strongest predictors of the time actually spent on gaming (Jansz and Tanis, 2007). On a broader level, the user's feeling of playing against an opponent is likely to evoke a social-competitive situation that should be capable of engaging and involving the user (Vorderer et al., 2003). Empirical game experiments have shown that competition and challenges in the game motivate students to achieve better performance during a web-based problem-solving activity (Hwang et al., 2012). However, in multiplayer browser games, the social relationships involved in game play seem to be more important than competition, in comparison to other game types (Klimmt et al., 2009). As a consequence of the above research, we infer that while social elements of game play might be a significant driver of game performance, it remains to be compared empirically whether people perform better in cooperative or in competitive modes of game play. Taking the above together, we formulate our first hypothesis as:

Hypothesis 3.1: Game players in a cooperative game mode have a better performance than when playing in competitive game mode.

Several studies indicate gender differences in digital gaming engagement and performance. Gender has revealed to be a significant indicator of video gaming engagement: males are almost twice as likely to be engaged in gaming as females (Hoffman and Nadelson, 2010). Female respondents' ratings of fictional video games demonstrated that lack of meaningful social elements, followed by violent content and sexual gender role stereotyping of game characters, were the most important reasons why females disliked the games. A second study revealed that female respondents were less attracted to competitive elements in video games, suggesting an explanation for gender-specific game preferences (Hartmann and Klimmt, 2006). Studies have found that games requiring specific cognitive skills - such as spatial attention, or spatio-temporal skills are received differently by males and females. For instance, first-person shooter action games have shown to appeal to boys rather than girls (Quaiser-Pohl et al., 2006; Terlecki and Newcombe, 2005). In pattern recognition tasks, by varying the number of figures in the pattern, studies suggest that males rely more on a match-jump strategy: once males have identified the matching target, they jump to the next problem without verifying the remaining stimuli, which presumably do not match, and thus progress through the test more quickly and have a chance to respond to more questions. In contrast, females tend to match every single figure to the target, even after identifying a match, and thus do not advance through the test as quickly, and often are unable to finish tests that have a fixed time limit (Glück and Fabrizii, 2010; Hirnstein et al., 2009). Hence, taking the above together, we expect that gender formation and the gender context, explain differences in game performance significantly. Based on the above research, we herewith derive our next hypothesis as follows:

Hypothesis 3.2: Male participants have a better game performance than female participants.

5.2.2 Personality Factors and Game Performance

Preference for a specific game playing mode, and the performance thereof, might be driven by personality-related factors. The first set of factors we consider is comprised of characteristics which are likely to remain (relatively) stable over time. To this end, we consider one characteristic each that may be mapped to competencies and regulation skills (Mischel and Shoda, 1995). Specifically, we consider (1) the characteristic of emotion regulation strategy, as a proxy for a regulation skill, and to be mapped later to the dynamic process of emotion and (2) the characteristic of need for cognition, as a proxy for understanding competencies, to be mapped later to the dynamic process of cognitive workload. In the following, we derive the corresponding hypotheses to study their relationships with game performance.

Emotion regulation strategies refer to the different ways in which response tendencies to an emotion may be modulated (Gross and John, 2003). Emotion regulation strategies may be broadly categorized as antecedent and response focused strategies, depending on when they occur in the emotion generative process. We focus on cognitive reappraisal and suppression as two representative strategies for each of the two categories. Cognitive reappraisal is an antecedent emotion regulation strategy that involves changing the way one thinks about a stimulus in order to change its affective impact (Buhle et al., 2014). Emotion suppression, on the other hand, is a response-focused strategy that aims at regulating emotions by suppressing those that have already emerged (Gross and John, 2003). Previous work has shown that the behavioral consequences of the two strategies are different. Reappraisal leads to enhanced positive emotion, less intensive negative emotion, and hence bears positive social consequences (Gross, 2002). Reappraisal strategy has been shown to be beneficial to decision-making, particularly in risky situations (Heilman et al., 2010). Suppression, on the other hand, masks social signals that would otherwise be available to partners, and can have adverse social consequences. Prior experimental research indicates that individuals who habitually suppress their emotions are less likely to share positive and negative emotions alike, and are associated with poorer social support (Gross, 2002). Thus, taking the above together, we hypothesize that the type of emotion regulation strategy (reappraisal/suppression) employed by a person, affects game performance, depending on the gaming context.

Hypothesis 3.3: Emotion regulation strategy moderates the impact of game context on game performance.

Need for cognition describes the willingness and the tendency of a person to engage in effortful cognitive activity, and plays a role in determining to which extent a person is motivated to engage in social activity (Kearney et al., 2009). In the realm of digital games, cognitive benefits of gaming have been cited as a strong reason for player performance. Games provide the player with a rich environment from which cognition is not only developed but also enhanced by the provision of input within the scenario itself (Smith, 2004). For example, (adolescent) gamers typically perform better on tests of processing speed and visuospatial functioning than non-gamers (Green and Bavelier, 2003). While several studies report the cognitive benefits of continuous gaming (Green and Bavelier, 2006) on different age groups (Allaire et al., 2013) and gender (Feng et al., 2007), so far there is little work that specifically explores the impact of need for cognition on players' performance in different modes. For instance, players with a higher need for cognition might only perform well if positively influenced by the gaming context. Hence we further explore this relation, how an individual's need for cognition is related to their performance levels in different game contexts.

Hypothesis 3.4: Need for cognition moderates the impact of game context on game performance.

5.2.3 Internal Processes and Game Performance

As the final set of factors that impact game performance, we next consider dynamic internal processes as influences on game behavior: namely affective and cognitive processes. To obtain a theoretical understanding of which processes underlie game performance, we orient ourselves to the dual processing theory. Briefly summarized, it states that individuals are primarily influenced by two systems: the deliberative and cognitive system, and the effortless and affective system. Lieberman (2007) posits that these two systems and the associated internal processes thereof determine how individuals experience and react to their environment. These two processes are modeled with the two proxies of emotional arousal and cognitive workload. Since games promise elements of enjoyment, game-playing is likely to be accompanied by sensory experiences in the form of arousal. In this paper, arousal is referred to as the intensity of affective processes accompanying game play. Arousal needs to be distinguished from flow theory, wherein a heightened arousal of sensory and cognitive stimulation could occur due to continuous engagement and complete absorption in the game (Csikszentmihalyi, 2000). While flow theory implies better game performance due to complete absorption in the game, arousal does not necessarily imply complete absorption, but may still influence game score.

Emotions of gratitude, sharing and giving, foster cooperative behavior, even when it is at the expense of individual benefits. While emotions of inhibition reduced cooperation, positive emotions increased cooperation (Rand et al., 2015). In other words, most cooperative individuals had high positive emotion and low inhibition, whereas reflective or deliberative processing may undermine cooperative behavior by suppressing the prosocial effects of positive emotion. Turning to the competitive context, competition is a powerful stimulus that can create emotional responses of arousal, manifesting both as heightened activity and motivation in the game, or even as rivalry (Vorderer et al., 2003). In an auction context, competition has shown to fuel arousal, which in turn impairs decision-making (Ku et al., 2005). In digital games, players who compete with opponents of similar skill levels tend to apply more effort, while playing against opponents with lower skills increases enjoyment and decreases arousal (Liu et al., 2013). Hence, in a competitive setting, arousal is additionally likely to impact game score. Taking the above together, along with the CAPS framework, it is likely that the level of emotional arousal drives performance, depending on whether a player is in cooperative or competitive mode, or whether the context is a male or a female setting. We formulate the next hypothesis as follows:

Hypothesis 3.5: Emotion mediates the impact of game context on game performance.

With regard to cognitive processes, we examine the impact of cognitive workload on game performance. Cooperative game-playing mode has been shown to demand far lesser (aggressive) cognition to be expended (Schmierbach, 2010). The impact of cognitive workload in a cooperative context comes with the mental cost of factoring in another person's behavior. However, providing cooperative assistance (through additional agents) might reduce the individual cognitive workload during a task. In competitive contexts, it has been shown that cognitive stress that occurs post-match is predictive of performance, as well as of subsequent stresses experienced (Scanlan and Lewthwaite, 1984). Taking the above together, it is likely that the level of experienced cognitive workload changes according to the cooperative and competitive setting, but it is not known whether it influences game performance positively or negatively, and if so, to what extent. Orienting to the CAPS framework, we hypothesize the mediating influence of the dynamic process of cognitive workload, as follows:

Hypothesis 3.6: Cognitive workload mediates the impact of game context on game performance.

5.3 Method

In the following section, we detail the experiment design, followed by the task description. The procedure and the measures to quantify the factors in the research model are then described.

5.3.1 Experiment Design

This study examines factors that explain performance differences in different modes of game play. We use a 2x2 within-subject design with the two treatment variables game playing mode and gender. The variable game playing mode has two levels, cooperative (COOP) and competitive (COMP) mode, where groups of two players interact. For the variable gender, we considered two levels of groupwise gaming between players: male-male and female-female. Homogeneity of group formation with respect to gender facilitates comparison of gender interactions. In all treatments, participants repeatedly played a pattern recognition game. To ensure comparability between treatments, the basic rules of playing were identical across treatments.

5.3.2 Description of Task

In order to operationalize the search task (individually, and as a group), we utilize a pattern recognition game, which is a common application domain of serious games. In order to maintain high levels of experimental control, we use a context-free version of pattern recognition. The game's objective was to identify the correct pattern from amongst 20 candidate patterns. To ensure consistency, playing time for each round was set to 7 seconds and the number of rounds played was held constant across participants and treatments. The patterns consisted of a sequence of 5 symbols (upward triangle, downward triangle, rhombus, square and circle). In each round of game play, the pattern to be identified was drawn without replacement from the 5 symbols, and the 20 candidate patterns were drawn from 120 (i.e., 5!) possible patterns with replacement.

The scoring rules - and consequently the payoff - differed between COOP and COMP treatments. In the COOP treatment, participants gained 5 points each for themselves and their partner for a correct click (henceforth referred to as a hit). Likewise, participants lost 5 points for themselves and their partner each in case of an incorrect click (henceforth referred to as a miss). By contrast, in the COMP treatment, participants gained 15 points for a hit, but the opponent lost 5 points. For a miss, the participant lost 15 points, but the opponent gained 5 points. In both treatments, participants were not penalized for refraining from clicking in a round (henceforth referred to as unclicked). Hence, in both treatments, participants' payoffs were dependent on their own performance as well as their partner's (opponent's) performance. Figure 5.2 shows one participant's' game screen for the COOP treatment, and the score table is given in Table 5.1. The COMP treatment screens were identical.

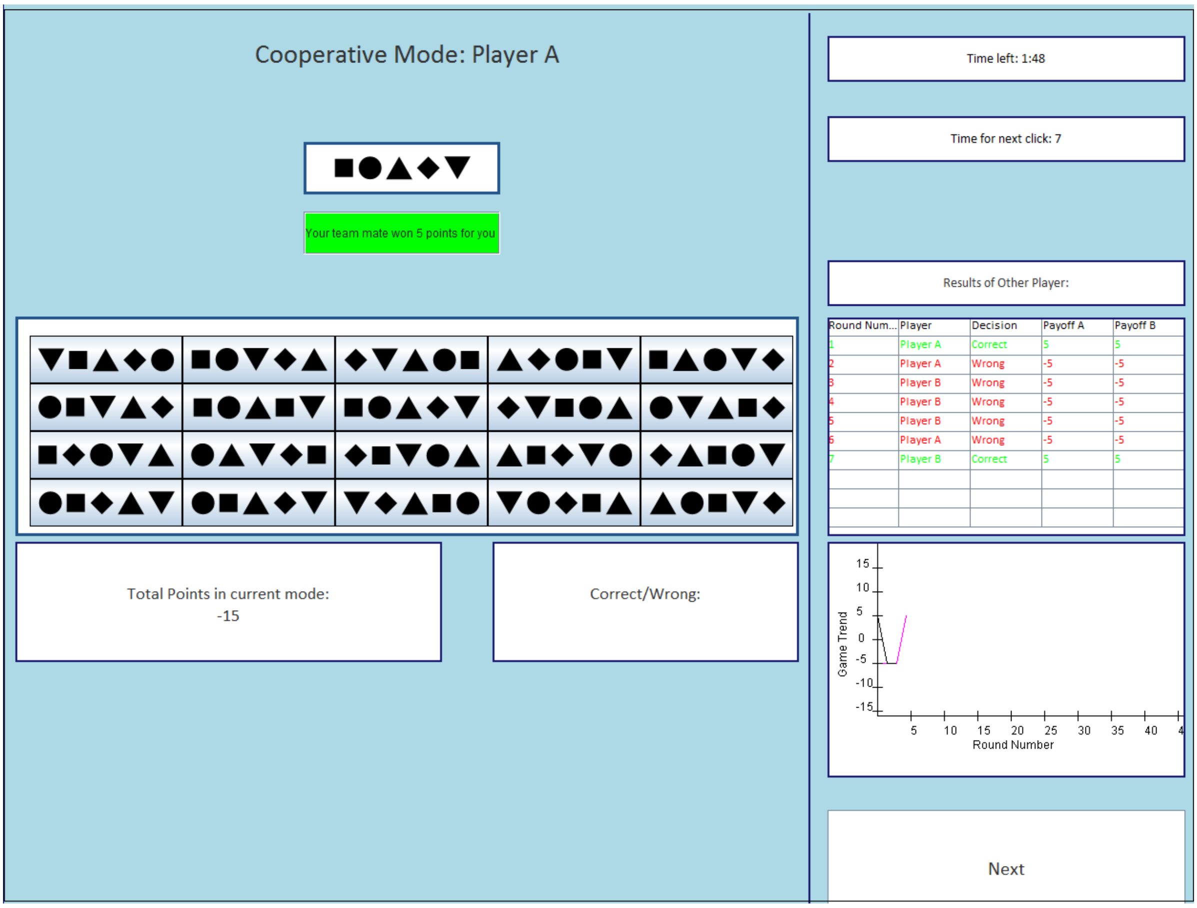


FIGURE 5.2: *Experiment Screenshot in Cooperative Mode*

In order to enhance participants' sense of cooperative and competitive gameplay, we included a performance history for participant and partner on the gaming screens that tracked game performance in each treatment. Performance was displayed both as a table (green text color - hits; red text color - misses; table on the middle right of the screens in Figure 5.2), and as a graph (bottom right of the screens in Figure 5.2). Participant's own performance was colored in black, and the partner's (opponent's) performance was colored in pink. In addition, a blinking message was shown below the search pattern after each clicking action. S/he would receive a blinking message on his/her screen with the message "Your partner (opponent) won/lost x points for you" if the partner (opponent) contributed to (reduced) his or her score. Finally, participants were shown the time available for each click as countdown of 7 seconds, and the time available in the current treatment as a countdown of 5 minutes.

TABLE 5.1: *Summary of scores for participants in the two treatments*

		Treatment	
		Cooperative Mode	Competitive Mode
		(Own, Partner)	(Own, Opponent)
Performance	Hit	+5, +5	+15, -5
	Miss	-5, -5	-15, +5
	Unclicked	0, 0	0,0

5.3.3 Procedure

The experimental procedure is depicted in Figure 5.3. In order to avoid potential carry-over effects, perfect stranger matching was employed. Participants were matched with different partners in cooperative and competitive modes. To control for order effects, treatment order A (COOP, COMP) was played in half the sessions while in the other half, treatment order B (COMP, COOP) was played. Prior to the experiment, participants received instructions in writing as well as in audio, about the pattern recognition task, the treatments, the scoring tables (including own and others' game performance), the performance history elements on the treatment screens and the perfect-stranger matching. To ensure that participants understood the instructions correctly, a short comprehension quiz was administered. This was followed by a training phase in which participants played the game in individual mode for 1 minute to familiarize them with the game.

The first treatment (COOP or COMP depending on treatment order) was then played for 5 minutes, thus permitting 42 rounds of gameplay of 7 seconds each and a corresponding number of clicks. The treatment was concluded by a result screen informing the participants of their game score and payoff. A subsequent pause of 30 seconds gave participants the opportunity to mentally disengage from the preceding treatment and prepare for the next treatment (COMP or COOP depending on treatment order). The second treatment was also played for 5 minutes, or 42 rounds, and concluded by a result screen for this treatment. Participants were then shown another screen with their overall payoff from both treatments. Thereafter, participants answered questionnaires on demographic data, emotion regulation strategies (Gross and John, 2003), need for cognition (Cacioppo and Petty, 1982), prosocial and intrinsic motivation (Grant, 2008); and emotion (Mano, 1991), and workload levels (NASA-TLX,Hart and Staveland (1988)) for each treatment. Finally, participants were paid out based on their game earnings (computed as 5% of the cumulative earnings in both treatments).

Finally, in addition to reports on cognitive workload, and emotional levels, psychophysiological measures of brain activity, HR, and SCR were captured via sensors. For measurement of brain activity, a 32-channel EEG device of Brain Products was used, to record the electrical activity in the outer layer of the brain, namely the cerebral cortex. Signals were sampled at 500 Hz, band-pass filtered at 0.01 to 100 Hz, and checked for eye-blink artefacts. The EEG Workload index mirrors the theoretical definition of cognitive workload, taking into account the absolute and relative power spectra from 1 to 40 Hz of EEG channel. For measurement of SCR and HR, Ag/AgCl electrodes were connected to the Bioplux (2007) sensor system, and transmitted via Bluetooth.

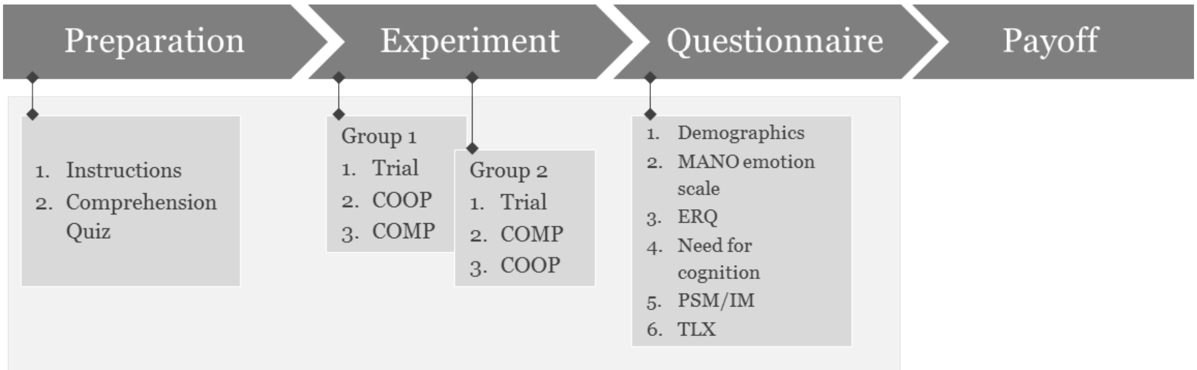


FIGURE 5.3: *Experiment Procedure*

In order to test participants' interaction with the experimental system, find potential flaws in the software, and parameterize the timer, a pilot study with 20 participants was conducted. Each session had 4 participants. The results of the pilot study indicated that participants indeed noticed the differences in game playing modes, and played differently depending on the social setting. In addition, 7 seconds was reported as being challenging, but as being exciting as well. Hence we retained our design choices in implementing the experiment with 7 seconds for each round of pattern recognition.

The main study was conducted with 156 participants. 76 were male and 80 were female. 4 participants were invited to all-male or all-female sessions. Overall, 39 experimental sessions were held. Participants were recruited using ORSEE (Greiner, 2004), filtering on gender. The study was conducted in compliance with the university's ethical guidelines.

5.3.4 Measures

We dummy-coded the treatment variables gender (male=0, female =1) and game-playing mode (COOP=0, COMP=1). We used four well-known and widely used self-reported scales to quantify personality-related characteristics and the internal processes.

For measuring the emotion regulation strategies of participants, we classified whether participants were primarily reappraisers or suppressors, by employed the emotion regulation questionnaire (ERQ) as described by (Gross, 2002). Emotion regulation strategies of participants were classified as reappraisal and suppression, based on their average scores in the 6 items for reappraisal, and 4 items for suppression. Participants' need for cognition was measured with the 18-item scale developed by (Cacioppo and Petty, 1982). The overall need for cognition score was then computed as the difference between the sum of scores on 9 positively correlated items, and 9 negatively correlated items to the underlying construct. The need for cognition score has a range of [-45, 45].

The internal processes were assessed with two self-reported measures. For assessing emotions experienced during game play, we used the scale developed by Mano (1991), of which 6 emotions were considered (active, aroused, nervous, surprised, excited, calm, and sleepy), once for each treatment (COOP and COMP). For measuring cognitive workload, we utilized a reduced version of the NASA-TLX scale (Hart and Staveland, 1988). In the context of our study, stationary digital gameplay, the dimension "physical demand" is not relevant and was thus omitted. The 5 remaining relevant dimensions are mental demand, temporal demand, performance, effort, and frustration. Participants provided their cognitive workload ratings for both treatments (COOP and COMP) and also reported their weights for each of these dimensions. The reported cognitive workload index was computed as a weighted mean of the scores on each of these 5 dimensions.

Finally, in order to quantify game performance in the two modes, we used three measures of game performance, namely hits (when the pattern was recognized correctly), misses (when the pattern is recognized incorrectly), and unclicked (when no pattern is clicked). While both the measures of hits and misses can be considered as willingness to expend effort, the measure of unclicked can be viewed as unwillingness to participate, possibly due to lack of time to find the pattern within the time, boredom, inattentiveness or due to loss aversion. The maximum number of clicks per treatment was 42 (each treatment lasted for 300 seconds / every 7 seconds another pattern was displayed). In a similar method, group performance was calculated as 42 possible clicks per treatment times the maximum group payoff (10 points) if both team members recognized the pattern correctly, bringing the maximum group payoff to 420 points in both game modes. In the following section, we proceed to test the proposed research model using the above measures.

5.4 Results

Figure depicts the distribution of participants' game performance in cooperative and competitive modes of game play. A preliminary analysis of the data with a repeated ANOVA showed that the means were significantly different for hits for the two game modes (F=1.442, p<.05) and significantly different for the two gender groups as well (F=7.704, p<.01). The means of misses and unclicked did not differ significantly between the two game modes, but only differed across the gender groups (Figure 4 depicts the corresponding charts). We examine differences in game performance in detail in the following.

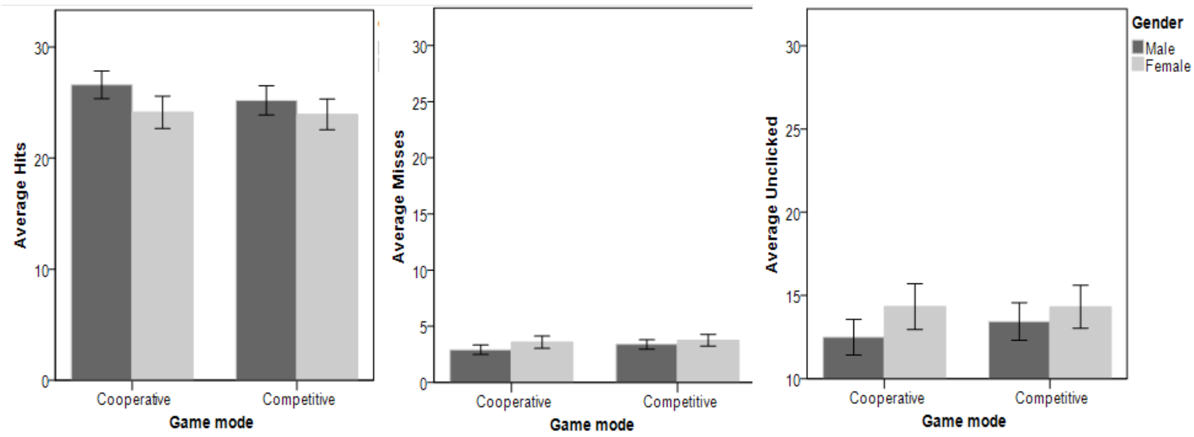


FIGURE 5.4: *Boxplot Distribution of game performance measures for game environments.*

5.4.1 Impact of game context on game performance

Table 5.2 shows the results of the logistic regressions. The response variable in regression I is the probability of the given click to be a hit, given the distribution function of these three measures (0-42). In regressions II and III, we conducted additional logistic regressions on the dependent variables "probability of misses" and "probability of unclicked" in the total number of trials. Regression I shows that participants had significantly fewer hits (B=-0.143, SE=0.052, p<.01) in competitive mode than in cooperative mode. Similar patterns were also visible for misses (B=.163, SE=.096, p<.10) and unclicked (B=.106, SE=.055, p<.10), with more misses and unclicked for competitive than in cooperative mode. Hence, we conclude that there are indeed significant differences in game performance with better performance in cooperative than in competitive mode, highlighting the important role of the interaction mode on game performance (H3.1). The difference in performance between the two modes is illustrated further in the following results as well.

TABLE 5.2: *Logistic Regression Results for individual game performance*

	Dependent Variable					
Independent Variable	Hits (I)		Misses (II)		Unclicked (III)	
Mode: Comp vs. Coop	-.143(.052)	**	.163(.096)	+	.106(.055)	+
Gender: Female vs. Male	-.262(.052)	***	.221(.096)	**	.220(.055)	***
Mode x Gender	.124(.073)	+	-.109(.132)		-.107(.077)	
Treatment Order: Coop/Comp vs. Comp/Coop	.145(.037)	***	.038(.066)		-.174(.038)	***
Constant	.487(.040)	***	-2.615(.076)	***	-.788(.042)	****
Nagelkerke R^2	0.156		0.043		0.129	

Note: +p<.1; *p<.05; **p<.01; ***p<.001. N=293 (156 participants*2 game modes=312, 19 data points were removed due to incomplete data in one or more of the questionnaires).

The effect of the gender setting that one is in, is significant across all three performance measures. Regressions I - III reveal that females had fewer hits, more misses and more unclicked, in comparison to males, all significant at the 0.001 level. This hence provides support for H3.2, that male participants have a better individual performance than female participants. This result is also confirmed by the regression in Appendix D (Table D.1), which summarizes the analogous result for group performance.

5.4.2 Impact of personality characteristics on game performance

We next turn to the moderating effect of the personality characteristics on game performance. To do this, we test for potential differences in performance, arising due to the interaction of emotion regulation strategy, and need for cognition, with the treatment factors. These results are summarized in Table 5.5 (for individual performance) and Appendix D, Table D.1 (for group performance). In the case of individual performance, it can be seen that reappraisers performed better and had more hits (B=.154, SE=.035, p<.001) and fewer unclicked (B=-.164, SE=.037, p<.001). Personality traits of suppression and need for cognition were, however, not significantly explaining individual game performance. Examining the interaction effects of the characteristics on game context, the only significant effect was that female reappraisers performed worse than male reappraisers, shown in fewer hits (B=-.082, SE=.038, p<.05), and more unclicked (B=.086, SE=.039, p<.05). Other interaction effects of personality characteristics (suppression, need for cognition) with game context were not significant predictors of individual performance. This hence provides support for H3.3, that personality traits of emotion regulation moderates the impact of game context on performance, whereas H3.4 is not supported.

TABLE 5.3: *Logistic Regression Results for individual game performance with personality characteristics*

	Dependent Variable					
Independent Variable	Hits (I)		Misses (II)		Unclicked (III)	
Mode: Comp. vs. Coop.	-.02(.206)	*	-.261(.382)		.116(.214)	
Gender: Female vs. Male	.361(.228)	***	-.374(.422)	***	-.268(.237)	***
Reappraiser score	.154(.035)	***	-.016(.066)		-.164(.037)	***
Suppressor score	.003(.034)		-.067(.062)		.02(.035)	
Need for cognition	-.001(.003)		0(.006)		.001(.004)	
Gender x Mode	.144(.081)	+	-.05(.142)		-.155(.085)	+
Mode x Reappraiser score	-.048(.035)		.026(.064)		.045(.036)	
Mode x Suppressor score	.011(.035)		-.001(.007)		-.041(.036)	
Mode x NCS	.005(.004)		.079(.062)		-.005(.004)	
Gender x Reappraiser score	-.082(.038)	*	.017(.07)		.086(.039)	*
Gender x Suppressor score	-.061(.036)	+	.156(.065)	*	.012(.038)	
Gender x NCS	-.006(.004)		-.004(.007)		.008(.004)	+
Treatment Order: Coop/Comp vs. Comp/Coop	.151(.037)	***	.05(.067)		-.184(.039)	***
Constant	-.232(.223)		-2.278(.417)	***	-.112(.233)	
Nagelkerke R^2	.39		.282		.318	

Note: +p<.1; *p<.05; **p<.01; ***p<.001. N=293 (156 participants*2 game modes=312, 19 data points were removed due to incomplete data in one or more of the questionnaires).

In the case of group performance (Appendix D,Table D.1), it can be seen that the impact of the personality characteristics are more pronounced than in the case of individual characteristics. Specifically, groups with a high aggregated need for cognition performed better in competitive mode, but worse in cooperative mode. Groups with high reappraisal scores performed better, whereas groups with high suppressor scores performed worse in both game modes. The interaction effects with gender are also significant predictors of group game performance. Specifically, female reappraisers had lower group performance than male reappraisers, in both cooperative and competitive modes, and this is visible in the individual performance as well. In addition, in competitive mode, female suppressors had better performance than male suppressors, and females with a high need for cognition performed better than males. Thus, this provides partial support for H3.3 and H3.4. However, this difference in influence between individual and group characteristics on game performance is an interesting one, and warrants further research.

5.4.3 Impact of internal processes on game performance

We next assess the influences of internal processes on performance, by examining the impact of emotional arousal and cognitive workload, as a theoretical approach to why performance differences might exist, due to the game context. Table contains the mediation analysis for H3.5 and H3.6. It can be seen here, that emotion indeed mediates the impact of game mode on game performance, leading to more hits ($B=.311$, $p<.05$), and fewer misses ($B=-.181$, $p<.05$) thus providing support for H3.5. However, a similar mediating effect of cognitive workload on game performance was not significantly visible in any of the performance measures (hits, misses, unclicked), thus invalidating H6. This result hence provides support for the notion that emotional processes underlie game performance, and explain differences that might arise due to the game context, whereas cognitive workload might not be an equally strong mediator. Comparing these results by splitting the data for the two gender treatment levels revealed that the mediation effect was acting in the same direction, and to a comparable effect size, across both genders, thus providing further support for H3.5.

We finally examine a variant of the last two hypotheses, H3.5 and H3.6, to test whether the personality characteristics moderate the mediating influence of the internal processes on performance. From Appendix D, Table D.2, it can be observed that participants with a higher reappraiser indeed impacted the mediating influence of emotion on game performance. Particularly, reappraisers with high emotion levels scored better than reappraisers

TABLE 5.4: *Mediation Analysis for Game Performance*

		Dependent Variable		
Hypothesis		Hits	Misses	Unclicked
			Estimate (Confidence Interval)	
H3.5: Emotion mediates the impact of mode on game performance	Direct effects	-1.122 (-2.498,0.277)	0.488 * (0.049, 0.942)	-0.133 (-.392, 0.045)
	Indirect Effects	-0.311 * (0.037, 0.706)	-0.181 * (-0.347, -0.047)	-0.133 (-0.392,0.045)
	Total Effects	-0.811 (-2.216,0.565)	0.307 (-.165,0.808)	0.459 (-.700, 1.582)
	Proportion Mediated	-0.267 (-3.806,4.317)	-0.475 (-7.542, 4.118)	-0.117 (-2.299,2.193)
H6: Cognitive workload mediates the impact of mode on game performance	Direct effects	-0.423 (-1.858,1.007)	0.242 (-.290,0.759)	0.182 (-1.198,1.403)
	Indirect Effects	-0.374 (-.850,0.035)	0.074 (-0.075,0.247)	0.182 (-1-119,1.403)
	Total Effects	-0.796 (-2.161,0.638)	0.316 (-0.185,0.806)	0.486 (-0.734,1.667)
	Proportion Mediated	0.335 (-5.830,4.274)	0.179 (-1.752,2.719)	0.319 (-5.884,6.317)

with a low emotion score. On the other hand, need for cognition was a significant moderator of cognitive workload when the score was 20 (towards the higher end of the scale). Thus, while the dynamic process of cognitive workload did not directly mediate the impact of mode on performance, taken together with the need for cognition score, led to significantly lower individual performance.

Figure 5.5 depicts how participants' correctness score varied with each position, amongst the possible 20 positions on the screen. As can be observed, participants had highest number of correct clicked, whenever the target pattern was at positions 0, 5, 10, 15, etc., i.e, the left-most position in a given row. This result is intuitive, since participants would normally search for patterns from left to right, thus denoting highest success rate whenever the position was in the left-most position. However, a regression analysis of the hits, on the position, revealed that the positioning of the target pattern was not necessarily significant, i.e., position alone was not sufficient to determine correctness of a hit.

Addressing the question, to which extent contextual and personality-related factors determine performance on a group level, we performed logistic regressions analogous to the above. Performance on the group level was measured in terms of group payoff. The dependent variable was the proportion of group payoff in the maximum possible group payoff. Since we used perfect stranger matching to re-match groups between treatments, we performed two separate regressions for each game-playing mode. Table 5.5 shows the logistic regressions on payoff in cooperative and competitive mode.

The results for gender and excitement are similar to those obtained on the individual level (Table 5.2). Excited groups earned, on average, higher payoffs (Table 5.5). Excited male groups performed better than excited female groups, and this also explains the gender difference in the payoff in both modes (Figure 5.6). Interestingly, personality characteristics which were not significant in explaining individual game performance turned out to be significant in explaining group game performance. High intrinsic motivation improved group performance in both modes, whereas high prosocial motivation was associated with worse group performance in the competitive mode and had no influence in cooperative mode. Groups with higher aggregate need for cognition scores performed worse in both cooperative and competitive modes. Higher aggregate suppression scores were related to worse performance across modes. Lastly, higher aggregated reappraisal scores led to better group performance in cooperative mode (B=0.039, SE=0.017, $p<.05$), and worse group performance in competitive mode (B=-.034, SE=0.014, $p<.05$). The latter is a surprising result, since reappraisers had a consistently better performance on the individual level.

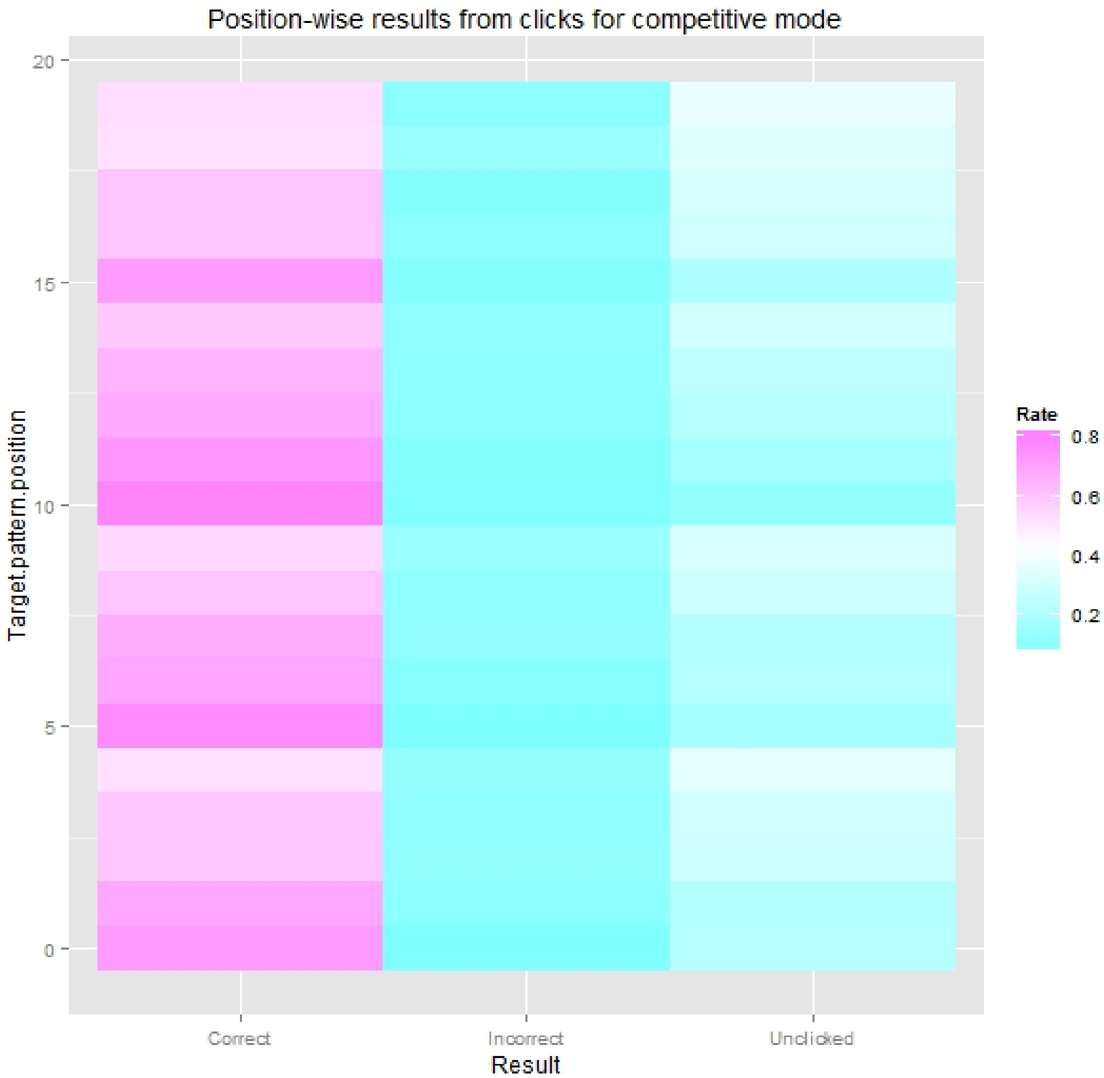


FIGURE 5.5: *Position-wise results from game clicks, in competitive mode*

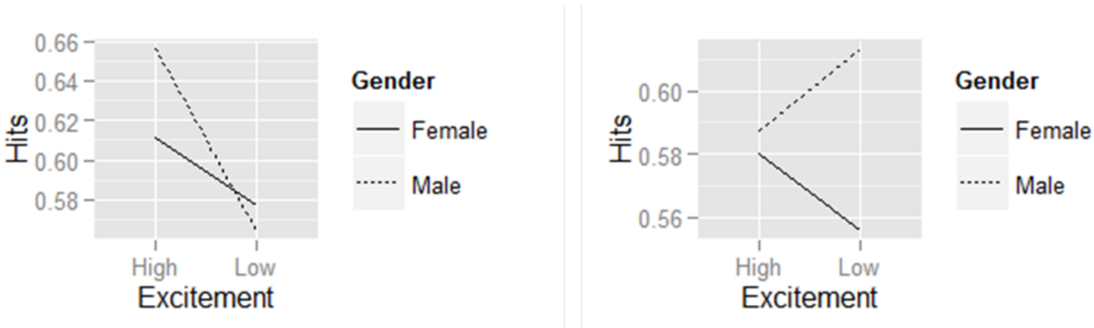


FIGURE 5.6: *Effect of Excitement on Female and Male Groups' Performance in (i) Cooperative Mode and (ii) Competitive Mode.*

TABLE 5.5: *Logistic Regression Results for Group Game performance*

	Payoff (Coop)	**Payoff (Comp)**
Gender: Female	0.194(0.099)*	0.400(0.090)***
Excited emotion score	0.095(0.011)***	0.053(0.009)***
Workload score	-0.006(0.005)	0.020(0.005)***
Reappraiser score	0.039(0.017)*	-0.034(0.014)*
Suppressor score	-0.043(0.016)**	-0.012(0.013)
Need for cognition score	-0.015(0.002)***	-0.013(0.002)***
Prosocial Motivation score	-0.020(0.016)	-0.117(0.011)***
Intrinsic Motivation score	0.124(0.014)***	0.032(0.012)**
Treatment Order: Comp-Coop	0.067(0.025)**	-0.157(0.021)***
Gender x Excited emotion score	-0.089(0.015)***	-0.099 (0.012)***
Constant	-0.628(0.167)***	0.308(0.136)*
N (Nagelkerke R^2)	70 (0.997)	72 (0.995)

While taking the arithmetic mean, might indeed be representative of the individual scores, it is possible, that the mean is not the only possible method to aggregate scores - both from a mathematical and from an applicability point of view. For instance, considering differences, ratios, or products of personality attributes, might be equally (or even more) informative, in understanding the impact of individual personality attributes on game performance. To this end, we compare how the different aggregate scores perform, in comparison to the arithmetic mean, for both the cooperative, and the competitive modes of play. Table 5.6 depicts these regressions.

It could be seen that, participants aggregated best, on the basis of their differences, in trying to explain performance in cooperative mode. While not true of all characteristics, it may be observed that in general, groups with larger differences in attributes, tended to perform worse (Excited, Reappraisal, Need for cognition, prosocial motivation) in cooperative mode. But what needs to be highlighted is that, models that looked at differences in attributes, performed the best in terms of Hosmer R^2 measure. On the other hand, in competitive mode, groups with higher mean scores, performed better, and in general, it was most informative to look at the average of scores (by means of the Hosmer R^2 masure), as a predictor for group performance. Hence it appears possible, that averages define performance in competitive mode much better, whereas differences explain cooperative behavior much stronger.

TABLE 5.6: *Influence of personality differences on payoff in cooperative (competitive) modes*

Attribute Difference	**Payoff (Coop)**	**Attribute average**	**Payoff (Comp)**
Dummy: female	-0.360 (0.025)***	Dummy: female	-0.349 (0.029)***
Dummy: order	0.036 (0.025)	Dummy: order	0.143 (0.026)***
Excited score	-0.087 (0.016)***	Excited score	-0.166 (0.008)***
Active score	0.024 (0.008)**	Active score	0.061 (0.009)***
Workload score	0.024 (0.008)**	Workload score	0.021 (0.005)***
Reappraiser score	-0.098 (0.028)***	Reappraiser score	-0.047 (0.017)**
Suppressor score	0.461 (0.030)***	Suppressor score	0.033 (0.017)*
Need for cognition	-0.027 (0.003)***	Need for cognition	-0.033 (0.002)***
Prosocial motivation	-0.063 (0.021)**	Prosocial motivation	-0.341 (0.014)***
Intrinsic Motivation	-0.010 (0.020)	Intrinsic Motivation	0.068 (0.014)***
Constant	0.328 (0.052)***	Constant	2.346 (0.160)***
Hosmer R^2	0.238	Hosmer R^2	0.228

5.5 Discussion

Our study contributes to understanding performance differences in cooperative and competitive serious games in a search context. Our aim was to define and understand the interplay of game contextual factors, personality-related factors (stable characteristics of emotion regulation, need for cognition respectively mapped to dynamic internal processes of emotional arousal and cognitive workload), and how these factors relate to individual and group game performance. We find that dynamic processes and stable characteristics of the individual as well as group characteristics play an important role in determining players' game performance in cooperative and competitive game play. These add weight to the cognitive-affective personality system (Mischel and Shoda, 1995) that advocates the study of context, dynamic processes, along with stable personality characteristics, to obtain a holistic picture with respect to behavior.

Specifically, we found that participants performed better in cooperative than in competitive mode, and males performed better than females, across all game performance measures, highlighting the role of contextual factors in defining game performance. Second, personality characteristics partially moderated this influence of context: reappraisers performed better, whereas other characteristics (of suppression and need for cognition) were only relevant on the group level. Third, our results indicate that dynamic factors, in particular affective processes, were important in determining game performance, leading to better game performance. Thus, emotional processes are an underlying (mediating) factor impacting game performance continuously. However, such an underlying mediating impact of cognitive workload was not visible.

Our results indicate that considering the emergence and regulation of both the dynamic process and stable characteristic with respect to affective processes is important when designing serious games, for individuals as well as for groups. As explanation for these results, with respect to characteristics, it appears that, by dealing with emotions before they arise (i.e., employing a reappraisal as an antecedent-focused emotion regulation strategy; (Gross and John, 2003), players are better able to focus on the game and on performance, which suggests that helping players to engage in reappraisal rather than suppression would be positive in terms of performance. Put differently, reappraisers and suppressors may have different game design requirements, to enhance their experience and game performance. Considering that it is not always feasible to train players in emotion regulation prior to game play, another option is to accommodate these different requirements by implementing adaptive games. It hence appears promising to further examine this relationship by means of neurophysiological evidence.

Need for cognition, as a characteristic, was more prominent on the group level, indicating that a group need for cognition index needs to be understood and evaluated as part of game design, in order to foster performance. In an organizational context, groups with high need for cognition, are expected to perform better in competitive than in cooperative mode, and hence, in this case, the game context would need to be chosen, based on the group characteristic. This would not only improve performance, but also address specific cognitive needs of individuals, in designing organization systems for collaboration, improving experience, and encouraging continuous usage.

Turning to dynamic processes, emotion was shown to mediate the influence of mode on performance, whereas individual cognitive workload was not significantly correlated with performance in either of the game playing modes. This result implies that experiential players are likely to perform better than players employing the slow and deliberative processes inducing cognitive workload. Our results imply that, although players might prefer games that induce high workload and cognitive challenges, such games might not necessarily be conducive to high performance. On the other hand, games which trigger emotional processes and create immersive experiences might be more effective in reaching a particular goal (whether it is in a serious game context or for an organizational purpose). Hence, in order to ensure continuous usage and meet the purpose of serious games, emotional and experiential needs of users are a primary factor. Finally, in the case of cognitive workload, the related stable characteristic of need for cognition was necessary to factor in, to understand the (negative) direction of impact of cognitive workload. This provides support to the CAPS framework, that it is quintessential to consider the impact of stable characteristics and dynamic internal processes together.

With regard to the comparison of influencing factors on individual and group performance, our results show that characteristics which were not significantly impacting individual performance were significant at the group level. Theoretically, this could be explained due to the fact that, personalities and processes of people often tend to have a compounding (or multiplying) impact, if positively correlated, and increase group performance. To this end, we investigated whether the aggregating method (of sum, product, ratio, or differences in personality traits) mattered, and whether each characteristic would need to be treated differently, in order to study the overall impact on behavior. Appendix D (Table D.3) contains the summary of these results. It can be observed, that in the case of cooperative mode, taking the difference between two attributes explained the group payoff best (in terms of model fit). In the case of competitive mode, however, taking the average of the individual scores of characteristics was most predictive of group payoff. Thus, the social presence of another individual is a powerful influence on the extent to which characteristics play a role, and the mode of interaction might determine how characteristics need to be aggregated. This particular result is noteworthy, and requires further research, since it highlights the importance of incorporating personality factors, based on the social context of a game, or even an organizational task, for instance.

5.6 Limitations and Future Work

This study is subject to limitations that need to be investigated in future work. First, to bring out the difference between stable characteristics and dynamic processes, in the case of characteristics, we performed a context-independent way of measuring these characteristics, whereas dynamic processes were measured in a context-dependent way (i.e., their emotions and cognitive workload in each of these modes). How continuously, and to what extent these characteristics are influenced, is a question that has not been regarded in this study, and needs to be regarded in future work, such as by using pre- and post- questionnaires. Second, we have only considered male-male and female-female interactions in our analysis, hence assuming homogeneity. It is very possible that male-female interactions would provide additional interesting insights on gender differences, and how these vary based on the gender composition of a group. Third, we intentionally used a context-free symbol recognition task in the experiment to avoid introducing confounding factors. Further research is required to examine how the effects in our study translate into specific application contexts (e.g., product search, image tagging), due to additional interactions between context of the application domain - for instance, (emotional) product or brand involvement - and the various factors investigated in our study. Fourth, group formation and group processes are very complex and highly dynamic; hence results from any group experiment need to be extrapolated very carefully to a real-world setting, e.g. a business context. To this end, different aggregation methods (such as taking the mean, product, sum or ratio of characteristics), will have to be considered carefully, while drawing conclusions about group performance. Finally, other aspects of game design will also have to be considered in future work - such as how humans perform with computers, and how the above factors are changed when interacting with computer agents (Teubner et al., 2015).

5.7 Conclusion

In this paper, we contribute to understanding which factors affect performance differences in a specific cooperative and competitive serious game, on the basis of contextual, personality-based and group formation attributes. Performance in games has shown to be reflective of performance in other contexts as well - for instance, games have been used to foster organizational change and development (Ruohomäki, 2003; McGonigal, 2011), and to nurture concepts of collaboration or a desirable level of competition. Performance differences in cooperative and competitive serious games have shown to depend on individual as well as group characteristics, hence these factors need to be considered to design user centric games and to improve performance in a serious games context.

Turning back to the question of cooperative and competitive decision processes posed in the beginning of this chapter, it appears quite strongly from the results of this study that cooperation is a context in which people perform better, in comparision to competition. The reasons thereof could be explained partially on the basis of personalities, gender, emotions and cognitive processes. Most importantly, the social setting was shown to determine, to which extent the personal attributes played a role, as well as the role of the internal processes in determining game performance. Thus, an undertstanding of this nature, of the influence of the external environment on internal processes, is only essential to better understand aspects such as willingness to perform, or cooperate, or to even quantify behavior. Designing systems which takes these into account, is hence a direct corollary, as a means to improving performance, and to also identifying proactively, the best way to group people for a common purpose, and potentially, to create better performing ecosystems, by means of identifying better-performing and better-fitting groups.

Chapter 6

Conclusions and future research

> “The ideal of behaviorism is to eliminate coercion: to apply controls by changing the environment in such a way as to reinforce the kind of behavior that benefits everyone.”
>
> B.F. Skinner (American Psychologist, 1904-1990)

6.1 Summary of Results and General Discussion

Studying decision processes from the point of how the decision environment impacts internal processes, enables the design of so-called human-centric systems, capable of understanding behavior as well as specific behavioral goals. As stated in the epigraph, understanding behavior would pave the way to designing systems for a specific behavioral goal, and one that maximizes common goals that benefits everyone, such as social welfare. In a similar spirit, Fogg (1998) coined the concept of persuasive technologies - technologies capable of motivating people towards a specific behavior, and triggering change in a specific manner. In the context of electronic markets, Weinhardt et al. (2003) write that when designing electronic markets, it is essential to consider influences that arise from technical fundamentals, as well as potential user requirements, business constraints, and economic objectives. Each of these influences has a profound impact on the outcome and, as a consequence, on the usability and the acceptance of the market (Weinhardt et al., 2003). This thesis contributes to engineering market systems by focusing on behavioral aspects during design, implementation, and evaluation. Specifically, this work attempts to quantify, to what extent external and internal influences impact economic decision-making; and applies these results to creating human-centric decision environments. In addition, we also define the need for, implement, and evaluate a platform to achieve behavioral studies of the afore-mentioned nature.

Three studies were undertaken, to examine the influences of the decision environment on behavior, and to study performance and deviations from expected behavior in each of these environments. In order to achieve this, a NeuroIS approach was adopted, the method which facilitates the integration of neuroscientific theories into the design of IT artefacts. We examined two internal processes using a NeuroIS approach - namely, *emotional arousal* and *cognitive workload*. Three types of external influences were examined - namely, *events* (such as gains and losses), *known parameters* (such as time available, and whether the individual is in a group or individual context), and *unknown parameters* (such as value uncertainty, and probability of occurrence of an event). In the process of implementing the above studies, we identified the lack of a suitable experimental platform that facilitates both behavioral and NeuroIS aspects. Therefore, our first challenge was to collect and describe the requirements for, and develop a platform to conduct behavioral studies empirically in a controlled environment. To this end, the design objective in this thesis was stated as follows:

- **DO: A freely available and extensible experimental platform that facilitates (i) experiments of individuals and groups, (ii) physiological measurements and time synchronization, and (iii) real-time integration of physiological data**

In order to identify and provide a technical solution that meets emerging requirements for conducting NeuroIS research, the platform Brownie was implemented as part of this thesis. Brownie stands for behavioral Research of grOups using Web and NeuroIS Experiments, and is a Java-based platform that may primarily be used to implement the interface elements, to model the decision environment being studied. Brownie also enables integration of NeuroIS specific measures, such as heart rate (HR), skin conductance response (SCR), Electroencephalography (EEG), and eye-tracking into one platform. Importantly, Brownie enables the incorporation of the upcoming feature of real-time physiological indicators such as live-biofeedback. These indicators may be integrated in studies to understand the impact of specific neurophysiological measures on decision behavior. With this platform, we help reduce both the effort and technical knowledge required to conduct

NeuroIS research, to a better manageable level. We also provide a high level of flexibility with regards to individual experimenters' needs, such as extensibility to emerging NeuroIS methodologies and scalability across various devices. Brownie contributes to research in studying decision making processes in the lab, as well as in designing and implementing experiments to study the interrelationships between decision environment and decision behavior.

We next addressed the research questions of this thesis, concerning the impact of decision environment on internal processes, and consequently on behavior. As the first research question, we aimed to understand expected value (EV) maximizing behavior in a trading context. We investigated whether adopting different emotion regulation strategies is accompanied by different levels of integral arousal, and has a significant role in explaining deviations from behavior as defined by expected-value maximization, particularly when experiencing gains and losses. Our first research question was stated as follows:

- **RQ1: In an individual context, do emotion-regulation strategies moderate the role of integral arousal on EV-maximizing behavior, particularly in dealing with the external influences of gains and losses?**

To this end, a single-decision trading experiment was implemented, where participants were subjected to a repeated single-decision trading experiment, along with questionnaires and physiological measures (HR and SCR). Participants' EV-maximizing behavior was recorded, by means of decisions to hold or keep the owned stock, after experiencing gains and losses.

The results showed that participants who predominantly employed the emotion regulation strategy of reappraisal ("reappraisers") exhibited lower integral arousal (measured in HR and SCR) than those who had a lower reappraisal tendency. On the other hand, those who employed suppression ("suppressors") had a higher integral arousal than those who suppressed emotions lesser. Reappraisers also made better decisions (in terms of EV maximizing) after experiencing losses than gains, whereas suppressors did not. Our study thus supports the notion that while reappraisal of negative emotions is beneficial for decision-making processes, suppression is not necessarily advantageous. In the future, it could hence be affirmed, if inducing emotion regulation strategies (of reappraisal) in decision-makers (such as traders and private investors) is associated with better decision-making performance. Such reappraisal-inducing techniques, might however need to be validated with additional psychophysiological measures such as illustrated by Astor et al. (2013a).

Turning to the second research question addressed in this thesis, we next attempted to quantify the experienced cognitive workload and emotional arousal, and examine how the auction environment moderates the impact of these internal processes on bidding behavior. To this end, we addressed the following research question:

- **RQ2: How do the external influences of specific auction elements (auction dynamics, value uncertainty) moderate the relation between internal processes (emotional arousal, cognitive workload) and bidding behavior?**

An auction experiment involving two auction formats (FPSB and Dutch auction), and utilizing psychophysiological measures of EEG and HR, was designed to investigate the above question. In the analysis, we attempted to understand, how the processes of cognitive workload and emotional arousal, impacted bidding behavior, based on deviations from a benchmark model (of RNNE strategy). Our results showed that arousal experienced due to Dutch auctions was significantly correlated with more deviations from RNNE bidding, whereas cognitive workload did not have a similar influence on bidding behavior. Hence, our results suggest that the presence of auction dynamics moderates only the impact of emotional arousal, to lead to more deviations from RNNE. Turning to value uncertainty, high value uncertainty impacted the effect of cognitive workload, leading to worse bidding behavior. In other words, under high value uncertainty, participants deviate more from RNNE strategy due to cognitive workload than emotional arousal. Choosing the right auction setting (such as the auction format, and the value uncertainty level) is therefore crucial to how the two processes of arousal and cognitive workload determine participants' bidding behavior. In addition, these pave way for understanding behavior in a specific decision environment, and designing systems that take the impact on internal processes into account, and motivate people towards a specific goal (Heilman et al., 2010; Eriksson and Sharma, 2003) - in this case, minimizing deviations from RNNE bidding strategy.

Turning to our third research question, we examined how the external factors (of which setting a person is in, whether cooperative or competitive), impacts performance in a given context. Whether one is able to perform well in a cooperative or competitive context, has often shown to be determined by the personality characteristics of a person, as well as the dynamic internal processes, namely, the emotional arousal and cognitive workload. We specifically explored the following:

- **RQ3: In a group context, how do external influences (cooperative and competitive game playing mode), and personality-related factors (characteristics and internal processes) impact individual and group game performance?**

We examined the personality-related factors in two social settings (cooperative and competitive). In a controlled laboratory experiment, participants played a pattern recognition game repeatedly, along with physiological measures (of EEG, HR and SCR) to measure internal processes. Our results showed that participants performed worse in competitive mode in comparison to cooperative mode, and male participants performed better than females, where performance was measured in terms of hits, misses and unclicked attempts in the game. Secondly, participants with a high reappraiser score performed significantly better in both cooperative and competitive modes, but other considered characteristics (namely, suppressor score, need for cognition) did not significantly impact individual performance. Emotions mediated the influence of game environment on performance, whereas cognitive workload did not have a similar impact. The results from a game performance context, may be transferred to organizational contexts and collaborative systems, in order to engage people in a particular task, for extended periods of time, or in retaining the attention of users and encouraging performance during the task. In addition, social settings could be appropriately chosen in a personality-specific manner, when they have to be grouped, in order to improve performance. Finally, experiential factors in a game could be focussed upon more, since these lead to improvements in game performance more readily than cognitive processes, specifically applicable to in effort tasks (Paolacci et al., 2010; Chandler and Kapelner, 2013).

6.2 Outlook and Future Research

We believe that our studies have contributed to a better understanding of the interplay between external and internal influences on decision behavior, taking both the cognitive and affective aspects into consideration. Being aware of both external and internal influences that shape human behavior and manifest as an action is proving to be increasingly valuable in the design of *decision support systems*. Decision support systems that analyze a broad range of information and enable managers to make business decisions more easily, are proliferating the business world (Chen et al., 2012). These tools and methods are turning to be vital to understand and meet customer ends to an unparalleled degree. Such systems aim to continuously monitor and support decisions, especially in dealing with market situations and business factors, which are beyond the control of the decision-maker.

Nevertheless, our research is subject to some limitations that need to be addressed in future research. The first one of these is that, in all the studies in this work, inferences have been drawn, on the basis of behavior in a laboratory setting. These results would hence have to be validated in external settings, by means of field experiments, to understand behavioral differences in environments without as much control as was established in the lab. Second, decision environments (of trading, auctions, and gaming) were predesigned environment, with a rather "simplistic" design, to achieve control of participants' decision environment, and to study influences on behavior. Transferring these results to a system design context, and examining whether the specific design changes in the decision environment, indeed correspond to the behavioral changes mentioned in these studies, remains to be addressed. Taking this a step further, such design changes could be achieved in real-time as well, as adaptive systems, which adapt according to users' current internal state. Third, subjects in these studies were students, and it remains to be validated, how the proposed models function across demographics, age groups, and cultures, that might further explain differences in decision behavior in further depth. Finally, in all the studies, further explanations of decision behavior arise when personality factors are taken into account. While we make a beginning in this direction by means of our experiments, several intricate issues remain to be addressed, in dealing with cognitive-affective aspects, along with personalities and stable characteristics.

Turning to future research, from a consumer perspective, the necessity to analyze and incorporate emotional aspects in individual decision-making, is being increasingly highlighted in recent literature (Fenton-O'Creevy et al., 2011; Fernández et al., 2010). On the one hand, interface design of financial decision makers could gain from the above NeuroIS studies, to improve user satisifaction as well as to enrich user experience (Riedl et al., 2014). On the other hand, individual decision support might be trained and achieved with NeuroIS methods, such as live biofeedback (Astor et al., 2013a), or by designing neuro-adaptive systems (Parsons and Reinebold, 2012). For instance, in a trading context, decision-makers may be shown live updates of their current excitement level using HR information, to help them be aware of their emotional states, and to make better decisions, in addition to taking the business factors, into account.

From a business provider perspective, the growing importance of business analytics, and their subfields, such as business intelligence have been subject to research for achieving competitive advantages, both from a technical and management perspective (Davenport and Harris, 2007). These tools and methods are turning to be vital to understand and meet customer ends to an unparalleled degree, and hence staying competitive as a business provider. In addition to enhancing consumer experience, we propose that NeuroIS methods could be integrated to the business and analytical world, in three specific ways.

We identify three possible ways of integrating the potential of NeuroIS methods: First, NeuroIS data could be used to enhance analytics of individual and group data from customers and employees. Second, NeuroIS data could provide live biofeedback to Business analytic systems in order to build user-adaptive business intelligence (BI) and business analysis and optimization (BAO) systems, wherein the user of the BI system is the decision maker as well. Third, experimental setups should be implemented in order to understand the user interaction of BI and BAO systems and NeuroIS data.

In the design of such systems, careful experimentation is an utmost prerequisite, in order to understand the impact of neuro- and bio- information on decision-making processes. To this end, we propose the use of the experimental platform Brownie, in order to conduct behavioral research of groups, on both web and NeuroIS interface designs. By collecting and analysing physiological data of participants in several decision contexts, it would be feasible to understand, at which stage of individual decision processes such neuro adaptive methods are required, and how these vary across individuals. Thus, these can subsequently be used for enhancing the decision support systems, and to foster better and emotionally aware decision-making.

6.3 Concluding Note

In this thesis, we detailed three studies to examine how the external environment impacts the role of internal influences on decision behavior. First, we saw that dealing with events of financial gains and losses, is better achieved by people who reappraise (cognitively alter the imapct of emotions, before they occur) their emotions. Second, we saw that different aspects of the environment, impacts different internal processes. Specifically, in an auction environment, auction dynamics altered the influence of emotional arousal, whereas value uncertainty altered the influence of cognitive workload, on decision behavior. Finally, in a game environment, we saw that, emotions mediated the influence of game mode (co-operation or competition), whereas, cognitive workload did not have a similar mediating effect. Thus, the emotional and experiential aspects of a game environment determined performance more strongly than the cognitive workload.

In addition, we developed and provided a Java-based platform Brownie, to systematically investigate questions of this nature: which external factors influence which internal processes, and how these in turn impact decision behavior, using a NeuroIS approach. We hope that the platform serves as a tool to address several behavioral questions, that may be better clarified with an understanding of the human self, using psychophysiological and NeuroIS methods.

Appendix A

Tutorials and Screencasts for Brownie

Screencasts for Brownie are available at the following URL's:

- Part 1: https://youtu.be/v4wSu_X7Zx8
- Part 2: https://youtu.be/urROSyWvwNw
- Part 3: https://youtu.be/uQRDPJxqP0s
- Part 4: https://youtu.be/_Ea8DCT4_Ds
- Part 5: https://youtu.be/q3fdlwXzgy8

Brownie's source code is availabe for download at: https://bitbucket.org/kit-iism Brownie's wiki, and tutorials are available at: https://bitbucket.org/kit-iism/experimenttool/wiki/Home

Appendix B

Instructions & Questionnaires

Experimentanleitung

1 Allgemeines

Willkommen zum heutigen Experiment und vielen Dank für Ihre Teilnahme. In diesem Experiment können Sie, abhängig von Ihren Entscheidungen, bares Geld verdienen. Bitte lesen Sie zunächst diese Instruktionen sorgfältig durch.

Wenn Sie Fragen haben, heben Sie bitte Ihre Hand und richten Sie Ihre Frage direkt und möglichst leise an die Experimentleitung. Kommunizieren Sie bitte für die gesamte Dauer des Experiments nicht mit den anderen Teilnehmern.

Das Experiment besteht aus **16 sich wiederholenden Runden**, wobei die erste Runde eine Testrunde ist. In der Testrunde können Sie sich mit dem Verfahren vertraut machen. In jeder Runde werden Sie eine Entscheidung treffen, durch die Sie in Besitz einer Aktie kommen. Im Anschluss können Sie sich entscheiden die Aktie zu halten oder zu verkaufen.

2 Ablauf einer Runde

Jede der 16 voneinander unabhängigen Runden besteht aus 4 einzelnen, wiederum voneinander **unabhängigen Aktieninvestitionen**.

Während einer Aktieninvestition wiederum durchlaufen Sie **2 Handelsperioden**. Ihre Auszahlung für die Aktie berechnet sich dann nach Ihrem Gewinn oder Verlust, den Sie in diesen 2 Perioden realisiert haben.

15 + 1 Runden (1. Runde = Testrunde) |
4 Aktien je Runde | 2 Perioden je Aktie

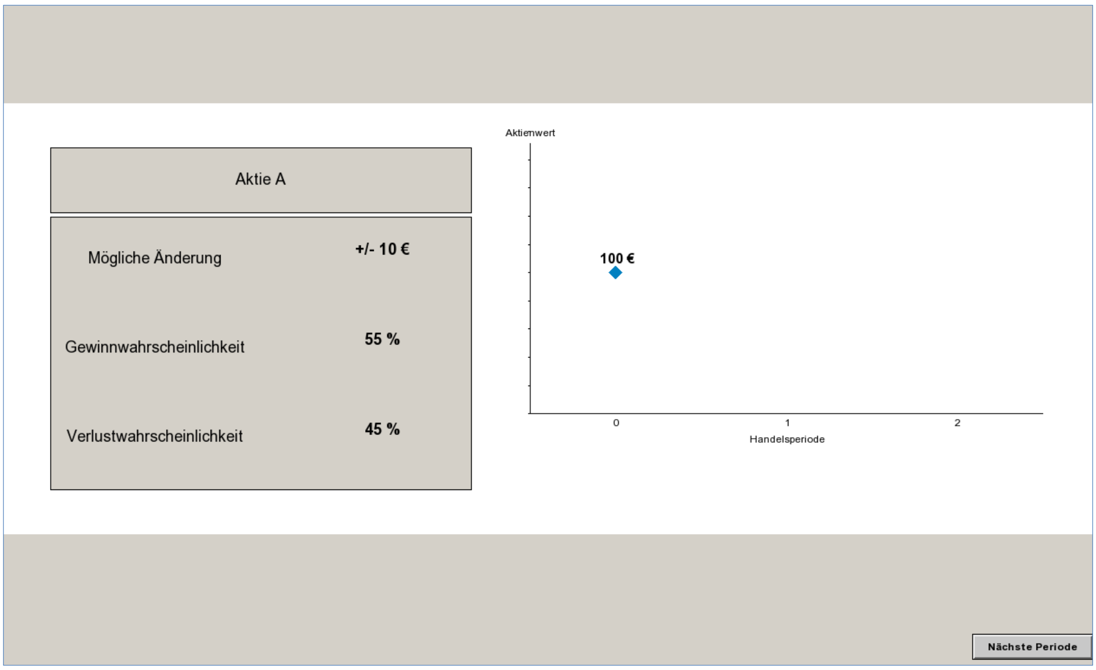
Die Schritte einer Aktieninvestition werden im Folgenden näher beschrieben.

2.1 Aktieninvestition

Zunächst haben Sie die Möglichkeit, eine von vier Aktien auszuwählen.

Jede Aktie im Wert von 100 € muss einmal pro Runde ausgewählt werden. Bereits ausgewählte Aktien sind nach dem Kauf rot hinterlegt (siehe Abbildung), sodass Sie diese in derselben Runde nicht mehr auswählen können.

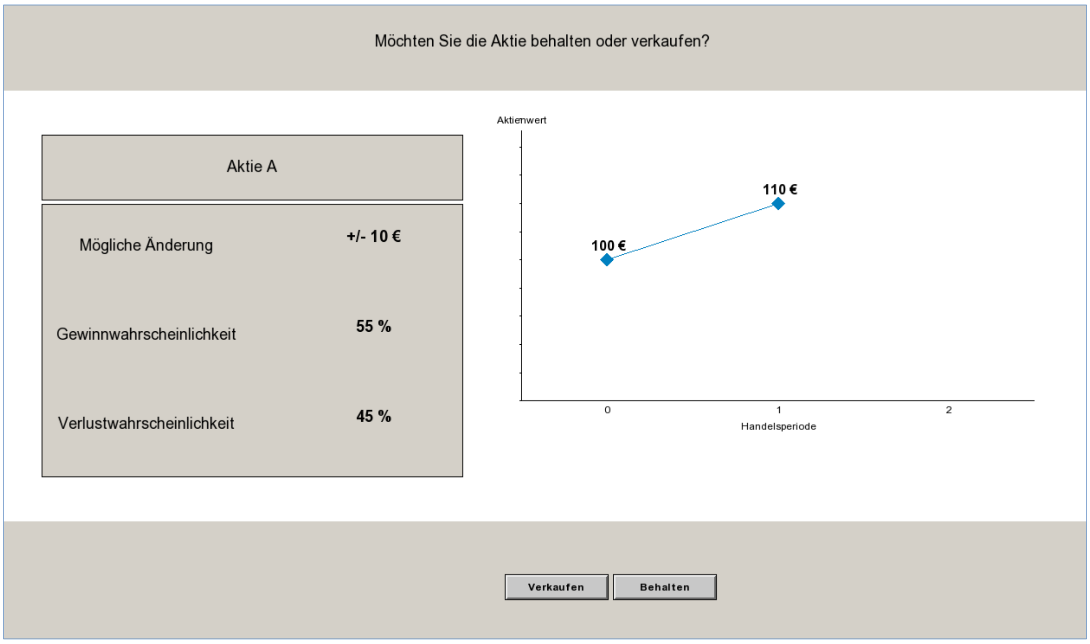
2.2 Handelsperiode 0 – Anzeige der Aktieneigenschaften



Im zweiten Schritt erhalten Sie, auf der linken Seite des Bildschirms, Informationen zur ausgewählten Aktie hinsichtlich ihrer möglichen Wertänderung (mögliche Werte: +/-2€, +/-10€), ihrer Gewinnwahrscheinlichkeit (mögliche Werte: 45%, 55%), sowie der sich daraus ergebenden Verlustwahrscheinlichkeit. Die Anzeige erfolgt jeweils mit kurzer zeitlicher Verzögerung. Auf der rechten Seite des Bildschirms befindet sich eine Graphik, die den Aktienwert (zu Beginn immer 100 €) zur jeweiligen Handelsperiode zeigt.

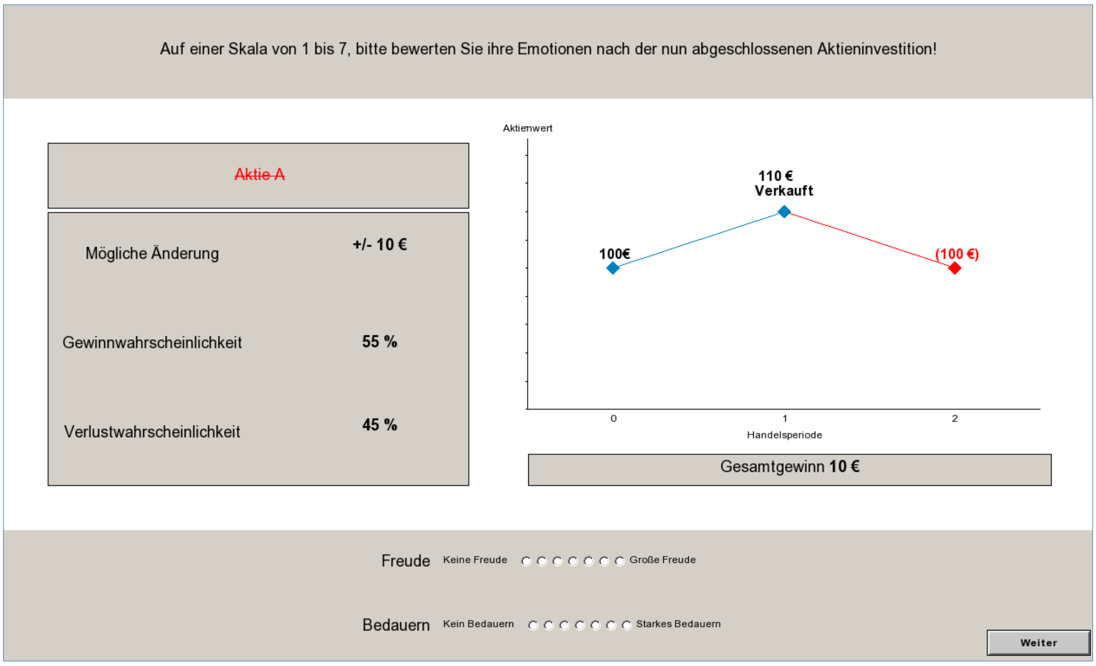
Im abgebildeten Beispiel ist der Betrag von 10 € die **mögliche Wertänderung**. Dann wird Ihnen mitgeteilt, wie hoch die **Wahrscheinlichkeit** ist, diesen Betrag zu **gewinnen**, im Beispiel sind dies 55 %. Mit einer 55 prozentigen Wahrscheinlichkeit gewinnen Sie also 10 €. Dies bedeutet jedoch auch, dass Sie mit 45 prozentiger Wahrscheinlichkeit 10 € **verlieren**.

2.3 Handelsperiode 1 – Aktienverlaufsinformation & Entscheidung



Am Ende der ersten Handelsperiode wird Ihnen die tatsächliche Entwicklung Ihrer Aktie dargestellt. Im Beispiel ist die Aktie um 10 € gestiegen. Jetzt ist es Ihre Entscheidung, diese Aktie jetzt zu verkaufen und einen Gewinn von 10 € zu realisieren, oder aber die Aktie zu behalten. Im Fall „Aktie behalten“ spielen Sie eine weitere Handelsperiode, danach wird die Aktie automatisch verkauft. Sie haben hierbei die Möglichkeit zu 55 % weitere 10 € zu gewinnen. Der Aktienkurs wird in jeder Periode fallen oder steigen, ein Gleichbleiben des Wertes ist nicht möglich.

2.4 Handelsperiode 2 – Abschlussinformation & kurzer Fragebogen



Nun sehen Sie das Ergebnis der Aktieninvestition: haben Sie die Aktie in Handelsperiode 1 behalten, sehen Sie hier, wie sich die Aktie verhalten hat und Ihren realisierten Gesamtgewinn. Haben Sie die Aktie in Handelsperiode 1 verkauft, sehen Sie hier den weiteren Aktienverlauf nur zur Information. Sie sehen dadurch, welchen Gewinn bzw. Verlust Sie realisiert hätten, wenn Sie die Aktie behalten hätten. Signalisiert wird der Verkauf der Aktie durch die Rotfärbung des Aktiennamens und des Aktienwertpunktes in der Graphik.

Im abgebildeten Beispiel haben Sie Ihre Aktie in Handelsperiode 1 verkauft, sodass Sie 10 € Gesamtgewinn realisiert haben. In Handelsperiode 2 sehen Sie, dass die Aktie gefallen ist. Hätten Sie die Aktie behalten, betrüge Ihr Gesamtgewinn 0 €.

Nach kurzer zeitlicher Verzögerung werden Sie im unteren Bereich des Bildschirms aufgefordert, Ihre momentan erlebten Emotionen direkt nach der Aktieninvestition auf einer Skala von 1 bis 7 zu bewerten.

3 Berechnung Ihrer Auszahlung

Ihre persönliche Auszahlung berechnet sich nach dem Gesamtgewinn oder -verlust **einer einzelnen Aktieninvestition**! Diese Aktieninvestition wählen Sie selbst nach dem Experiment durch Ziehen und Würfeln aus. Sie ziehen zunächst aus einem Umschlag eine Zahl von 1 bis 15, die Ihre Runde bestimmt (Testrunde ist ausgeschlossen) und anschließend würfeln Sie mit einem 4-seitigen Würfel um die Aktieninvestition innerhalb der gezogenen Runde um die zur Berechnung zugrunde liegende Aktieninvestition.

Zu Beginn erhalten Sie ein Guthaben von 22 €, sodass Sie im schlechtesten Fall auch bei einem Verlust von 20 € (10 € $_{\text{Verlust Periode 1}}$ + 10 € $_{\text{Verlust Periode 2}}$) immer noch eine Auszahlung von 2 € erhalten. Im besten Fall jedoch erhalten Sie maximal 42 € (10 € $_{\text{Gewinn Periode 1}}$ + 10 € $_{\text{Gewinn Periode 2}}$ + 22 € Guthaben).

Im gezeigten Beispiel ist die Aktie in Handelsperiode 1 um 10 € gestiegen, in Handelsperiode 2 um 10 € gesunken, sodass Ihr Schlusswert, gleich dem Anfangswert, 100 € beträgt. Da Sie nach Periode 1 verkauft haben, realisieren Sie aber einen Gewinn von 10 €. Dieser Gewinn wird zu den 22 € Guthaben addiert, sodass Ihre Gesamtauszahlung im Beispiel 32 € betragen würde. Schematisch sieht dies so aus:

Auszahlungskalkulation für gezeigtes Beispiel

Guthaben =	22 €	
+ Gewinn aus Handelsperiode 1 =	10 €	*Verkauft!*
(- Verlust aus Handelsperiode 2 =	10 €)	*nicht realisiert, da verkauft*
Auszahlungsbetrag =	**32 €**	

4 Schlussbemerkungen

Bitte füllen Sie nun nach Aufforderung den kurzen Verständnisfragebogen am PC vor Ihnen aus. Warten Sie dann, bis die Experimentleitung Sie dazu auffordert, das Experiment am PC vor Ihnen zu beginnen. Nach Abschluss dieses Experiments am Computer werden wir Sie bitten, einen Fragebogen auszufüllen. Nach Beendigung dessen werden Sie einzeln von der Experimentleitung zur Auszahlung gebeten, um durch Würfeln Ihre persönliche Auszahlung zu bestimmen und sich den Betrag auszahlen zu lassen. Das Experiment ist damit für Sie beendet.

Wenn Sie eine Frage haben, bleiben Sie bitte ruhig sitzen und heben Sie Ihre Hand. Der Experimentleiter wird dann zu Ihnen kommen und Ihre Frage beantworten.

Nachbefragung

Bitte geben Sie hier
Ihre PC-Nummer an: _____

Fragebogen 1

Wie alt sind Sie?

____________ Jahre

Sind Sie

☐ männlich

☐ weiblich

Studieren Sie ein Fach mit wirtschaftswissenschaftlicher Ausrichtung?

☐ ja

☐ nein

Haben Sie schon einmal an Experimenten mit physiologischen Messungen teilgenommen?

☐ ja

☐ nein

Haben Sie bereits an Aktien-Experimenten teilgenommen?

☐ ja

☐ nein

Wie schätzen Sie Ihre Kenntnisse im Bereich Aktienmärkte ein?

☐ Experte

☐ Grundkenntnisse

☐ Laie

Fragebogen 2

Wir möchten Ihnen gerne einige Fragen zu Ihren Gefühlen stellen. Uns interessiert, wie Sie Ihre Gefühle unter Kontrolle halten, bzw. regulieren. Zwei Aspekte Ihrer Gefühle interessieren uns dabei besonders. Einerseits ist dies Ihr emotionales Erleben, also was Sie *innen* fühlen. Andererseits geht es um den emotionalen Ausdruck, also wie Sie Ihre Gefühle verbal, gestisch oder im Verhalten nach *außen* zeigen. Obwohl manche der Fragen ziemlich ähnlich klingeln, unterscheiden sie sich in wesentlichen Punkten. Bitte beantworten Sie die Fragen, indem Sie folgende Antwortmöglichkeiten benutzen.

1--------------2--------------3--------------4--------------5--------------6--------------7

stimmt überhaupt nicht	**neutral**	**stimmt vollkommen**

1. ______ Wenn ich *mehr positive* Gefühle (wie Freude oder Heiterkeit) empfinden möchte, ändere ich, woran ich denke.

2. ______ Ich behalte meine Gefühle für mich.

3. ______ Wenn ich *weniger negative* Gefühle (wie Traurigkeit oder Ärger) empfinden möchte, ändere ich, woran ich denke.

4. ______ Wenn ich *positive* Gefühle empfinde, bemühe ich mich, sie *nicht* nach außen zu zeigen.

5. ______ Wenn ich in eine stressige Situation gerate, ändere ich meine Gedanken über die Situation so, dass es mich beruhigt.

6. ______ Ich halte meine Gefühle unter Kontrolle, indem ich sie *nicht* nach außen zeige.

7. ______ Wenn ich *mehr positive* Gefühle empfinden möchte, versuche ich über die Situation anders zu denken.

8. ______ Ich halte meine Gefühle unter Kontrolle, indem ich über meine aktuelle Situation anders nachdenke.

9. ______ Wenn ich *negative* Gefühle empfinde, sorge ich dafür, sie *nicht* nach außen zu zeigen.

10. _____ Wenn ich *weniger negative* Gefühle empfinden möchte, versuche ich über die Situation anders zu denken.

Fragebogen 3

Anleitung

Auf Ihrem Entscheidungsblatt sind auf der linken Seite zehn Entscheidungen aufgelistet. Jede Entscheidung besteht aus der Wahl zwischen „Option A“ und „Option B“. Insgesamt müssen Sie zehn Entscheidungen treffen und diese in der letzten Spalte eintragen. Am Ende des Experiments wird jedoch nur **genau eine** Ihrer Entscheidungen ausgewählt, die dann ausgezahlt wird.

Das auszahlungsrelevante Ergebnis wird mit einem zehnseitigen Würfel bestimmt; die Seiten sind nummeriert von 0 – 9 (die Zahl „0“ soll die „10“ repräsentieren.) Nachdem Sie Ihre zehn Entscheidungen getroffen haben wird der Würfel zunächst geworfen, um zu bestimmen, welche der zehn Entscheidungen für die Auszahlungsberechnung herangezogen wird. Danach wird der Würfel noch einmal geworfen, um die Auszahlung in Option A oder B zu bestimmen.

Sehen Sie sich nun die erste Reihe an. Option A bringt Ihnen 2,00 € falls der zehnseitige Würfel 1 zeigt und 1,60 € falls der Würfel 2-10 (0) zeigt. Mit Option B können Sie 3,85 € gewinnen falls der Würfel 1 zeigt und 10 Cent falls der Würfel 2-10 (0) zeigt. Die anderen Entscheidungen sind ähnlich, wobei in jeder Reihe bei beiden Optionen die Chancen, die höhere Auszahlung zu erreichen, steigen. Schließlich, bei der zehnten Entscheidung (in der letzten Reihe), wird der Würfel nicht benötigt, da jede Option die höhere Auszahlung garantiert.

Sie können Ihre Entscheidung in einer beliebigen Reihenfolge treffen und auch nachträglich noch ändern. Bei der Auszahlung haben Sie dann die Möglichkeit, zweimal zu würfeln, um die auszahlungsrelevante Entscheidung zu bestimmen. Ihr Gewinn (in €) bei dieser Entscheidung wird zu Ihren vorherigen Gewinnen hinzuaddiert und die Summe dann ausgezahlt.

Haben Sie noch Fragen? Sie können nun beginnen Ihre Entscheidungen zu treffen. Bitte sprechen Sie währenddessen mit Niemandem; wenn Sie eine Frage haben, heben Sie bitte einfach Ihre Hand.

Entscheidungsblatt

Option A	Option B	Ihre Wahl
1/10 Chance auf €2.00; 9/10 Chance auf €1.60	1/10 Chance auf €3.85; 9/10 Chance auf €0.10	
2/10 Chance auf €2.00; 8/10 Chance auf €1.60	2/10 Chance auf €3.85; 8/10 Chance auf €0.10	
3/10 Chance auf €2.00; 7/10 Chance auf €1.60	3/10 Chance auf €3.85; 7/10 Chance auf €0.10	
4/10 Chance auf €2.00; 6/10 Chance auf €1.60	4/10 Chance auf €3.85; 6/10 Chance auf €0.10	
5/10 Chance auf €2.00; 5/10 Chance auf €1.60	5/10 Chance auf €3.85; 5/10 Chance auf €0.10	
6/10 Chance auf €2.00; 4/10 Chance auf €1.60	6/10 Chance auf €3.85; 4/10 Chance auf €0.10	
7/10 Chance auf €2.00; 3/10 Chance auf €1.60	7/10 Chance auf €3.85; 3/10 Chance auf €0.10	
8/10 Chance auf €2.00; 2/10 Chance auf €1.60	8/10 Chance auf €3.85; 2/10 Chance auf €0.10	
9/10 Chance auf €2.00; 1/10 Chance auf €1.60	9/10 Chance auf €3.85; 1/10 Chance auf €0.10	
10/10 Chance auf €2.00; 0/10 Chance auf €1.60	10/10 Chance auf €3.85; 0/10 Chance auf €0.10	

Instructions

Welcome to the experiment! In this experiment, you will earn money **in cash**. How much you earn, will depend on your decisions, as well as the decisions of other participants. Please read through these instructions carefully. In case of questions on the experiment, please raise your hand to ask the experimenter.

In this experiment, you will participate as a bidder, in 20-40 auctions.

The Auction

In every auction a fictitious good will be auctioned. From the beginning of every auction, you will be shown the information on price of the good in the form of an approximate market price (private signal). You will also receive the information „error term“, which shows the interval with which the real value of the good can differ from the “private signal”. You and two other virtual participants are bidders in this auction. Each bidder bids a single value, without knowing the bid of other bidders. The bid will be entered manually using the keyboard, and will be submitted by clicking the button “Place bid”.

You will play two types of auctions, the „Dutch auction“, and the „First-price sealed-bid auction“. In the Dutch auctions, there is a clock ticking downwards, indicating the price of the good. **The Dutch auction comes to an end, as soon as the first bidder has placed a bid.** This bidder receives the good and pays his bidding price. **The first-price sealed-bid auction comes to an end, as soon as all the bidders have placed a bid.** Here the bidder with the highest bid wins the good, and pays his bidding price. If two bidders in the first-price sealed-bid auction have the same highest bid, one of the two bidders will be randomly picked as the winner by the experimental software.

The real value and interval of possible bids

In every auction interval of possible bids is between 15 MU (Monetary Units) to 100 MU. Every bidder can only enter bids in this range. The real value of every good may be equally distributed in this interval, which will not be shown to the bidders. In the experiment, you will be informed of the “private signal”, as well as the “error term”.

Error Term and Private Signal

„ Error term“ refers to the fact, how much the „Private Signal“ can differ from the real value. The possible values for the error term are 3 MU and 12 MU. All bidders receive the same error term in each round. The information “error term” is however drawn randomly for each bidder, from the range of the error term.

Note: In the final questionnaire, instead of the term „Error Term“, the terms „low variance“(3 MU) und „high variance“(12 MU) will be used.

Example

In the beginning of an auction, an „error term„ of 3 MU and a „private signal„ of 40 MU are provided. You can estimate the real value of a good and enter a corresponding bid. **The real value of a good lies between the difference of the private signal and the error term (40 MU – 3 MU = 37 MU) and the sum of the private signal and the error term (40 MU + 3 MU = 43 MU).** The real value of the good hence lies between **[37, 43]** (Figure 1).

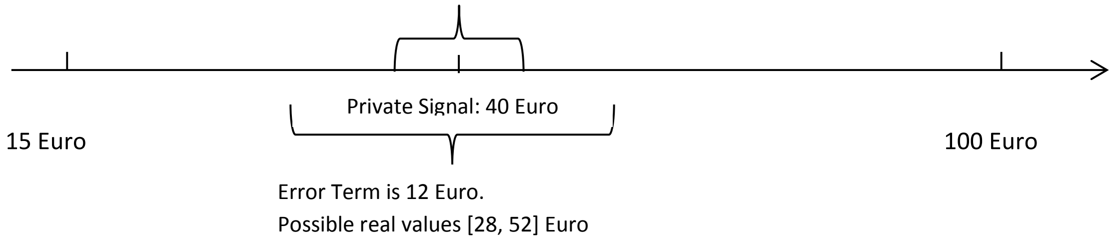


Figure 1. Error term and private signal

The payoff

A lost auction earns a payoff of zero. Upon winning an auction, you will receive the payoff of the winner, i.e., the highest bidder, as follows:

Payoff = Real Value – Buying price

<u>Numerical example to illustrate the payoff:</u>

Given that the real value of the good is 43.00 MU and you are the highest bidder in the course of the auction. You are therefore the winner of the auction, and you will pay as buying price an amount equal to your bid. Now, you have the following payoff situations:

(1) You bid above the real value, e.g. 60.50 MU

➔ You receive a negative payoff of 43.00 MU – 60.50 MU = -17.50 MU

(2) You bid exactly the real value, i.e. 43.00 MU

➔ You receive a payoff of 43.00 MU – 43.00 MU = 0.00 MU

(3) You bid below the real value, e.g. 42.00 MU

➔ You receive a payoff of 43.00 MU – 42.00 MU = 1.00 MU

If you did not win the auction, you earn neither a positive nor a negative payoff (i.e., 0 MU).

Course of the experiment

In this experiment you will take part totally in 20 to 40 auctions. The first auctions are only for trial, and are not payoff-relevant. These trial rounds are for undertanding the experiment course better. The following 20 to 40 auctions are payoff-relevant. The results of one auction have no effect on the result of the subsequent auctions.

Your account

In the beginning of every experiment every bidder has an account, with an initial deposit of 20€. On this account, the experiment software calculates your payoffs (positive and negative), which you achieve during the 20-40 payoff-relevant auctions. Your cumulative payoff is multiplied by a conversion factor of 0.05 and is added to the 20€ and will be paid to you after the experiment as cash. If your cumulative payoff for all auctions is 50.00 MU, for instance, in this case your account balance would be:

20 € + 50.00 MU * 0.05 = 22.5 €. A negative account balance will not be demanded from you.

Concluding remarks

We are happy to answer any questions regarding these instructions. The better you understand the instructions, the more money you can earn. Questions about bidding strategies will not be answered.

Before the experiment starts, you will be first asked comprehension questions about the rules of this experiment on your screen. Please enter the respective answers on your computer. At the end, two auctions take place as described above in a trial run. Then the actual experiment begins.

EEG is a method of medical diagnostics and neurological research for measuring the electrical activity of the brain by recording the voltage variations at the head surface. It is an established method of examination in neurology. The EEG measurements in our experiment are used for the recording of brain activity of the participants. The collection of data is realized by a hat with electrodes that is worn by the participant. After attaching the cap a harmless water-based connectivity gel is filled into the electrode to improve the conductivity of the scalp.

The EEG recording is highly prone to artifacts, since data can be affected by external sources, such as noise or unnecessary muscular movements. Therefore, we request you to avoid unnecessary movements as much as possible during the experiment.

If you have additional questions during the experiment, please be seated at your place and give the experimenter a hand signal. Please wait until the experimenter is at your place, and then ask your question as quietly as possible. Please remain seated at the end of the experiment and wait for further instructions of the experimenter. Please feel free to make notes on the notepad lying ready during the experiment. Participant instructions and the notepad are to remain at your place after the experiment.

Bitte geben Sie hier Ihre Teilnehmer-Identifikation an:

Befragung

Fragebogen 1

Wie alt sind Sie?

___________ Jahre

Sind Sie

☐ männlich

☐ weiblich

Studieren Sie ein Fach mit wirtschaftswissenschaftlicher Ausrichtung?

☐ ja

☐ nein

Haben Sie schon einmal an Experimenten mit physiologischen Messungen teilgenommen?

☐ ja

☐ nein

Haben Sie bereits an Auktion-Experimenten teilgenommen?

☐ ja

☐ nein

Wie schätzen Sie Ihre Kenntnisse im Bereich Auktion ein?

☐ Experte

☐ Grundkenntnisse

☐ Laie

Bitte beschreiben Sie Gedanken und Gefühle zu den eben durchgeführten Auktionen:

Allgemein

Befragung

Fragebogen 2

Wir möchten Ihnen gerne einige Fragen zu Ihren Gefühlen stellen, die Sie bei der Teilnahme an den eben durchgeführten Auktionen empfinden. Bitte beantworten Sie die Fragen, indem Sie folgende Antwortmöglichkeiten benutzen.

1---------2---------3---------4---------5---------6---------7---------8---------9---------10---------11

überhaupt nicht **neutral** **sehr stark**

________	Aktiv/Rege *(Active)*	________	Erregt/Begeistert *(Excited)*
________	Erregt/Aufgeregt *(Aroused)*	________	Änstlich *(Fearful)*
________	Ruhig *(Quiet)*	________	Gelassen *(Calm)*
________	Nervös *(Nervous)*	________	Schläfrig *(Sleepy)*
________	Überrascht *(Surprised)*	________	Zufrieden/Befriedigt *(Satisfied)*
________	Träge *(Sluggish)*	________	Glücklich *(Happy)*
________	Besorgt (Anxious)	________	Unglücklich *(Unhappy)*

Befragung

Fragebogen 3

Anleitung

Auf Ihrem Entscheidungsblatt sind auf der linken Seite zehn Entscheidungen aufgelistet. Jede Entscheidung besteht aus der Wahl zwischen „Option A“ und „Option B“. Insgesamt müssen Sie zehn Entscheidungen treffen und diese in der letzten Spalte eintragen. Am Ende des Experiments wird jedoch nur **genau eine** Ihrer Entscheidungen ausgewählt, die dann ausgezahlt wird.

Das auszahlungsrelevante Ergebnis wird mit einem zehnseitigen Würfel bestimmt; die Seiten sind nummeriert von 0 – 9 (die Zahl „0“ soll die „10“ repräsentieren.) Nachdem Sie Ihre zehn Entscheidungen getroffen haben wird der Würfel zunächst geworfen, um zu bestimmen, welche der zehn Entscheidungen für die Auszahlungsberechnung herangezogen wird. Danach wird der Würfel noch einmal geworfen, um die Auszahlung in Option A oder B zu bestimmen.

Sehen Sie sich nun die erste Reihe an. Option A bringt Ihnen 2,00 € falls der zehnseitige Würfel 1 zeigt und 1,60 € falls der Würfel 2-10 (0) zeigt. Mit Option B können Sie 3,85 € gewinnen falls der Würfel 1 zeigt und 10 Cent falls der Würfel 2-10 (0) zeigt. Die anderen Entscheidungen sind ähnlich, wobei in jeder Reihe bei beiden Optionen die Chancen, die höhere Auszahlung zu erreichen, steigen. Schließlich, bei der zehnten Entscheidung (in der letzten Reihe), wird der Würfel nicht benötigt, da jede Option die höhere Auszahlung garantiert.

Sie können Ihre Entscheidung in einer beliebigen Reihenfolge treffen und auch nachträglich noch ändern. Bei der Auszahlung haben Sie dann die Möglichkeit, zweimal zu würfeln, um die auszahlungsrelevante Entscheidung zu bestimmen. Ihr Gewinn (in €) bei dieser Entscheidung wird zu Ihren vorherigen Gewinnen hinzuaddiert und die Summe dann ausgezahlt.

Haben Sie noch Fragen? Sie können nun beginnen Ihre Entscheidungen zu treffen. Bitte sprechen Sie währenddessen mit Niemandem; wenn Sie eine Frage haben, heben Sie bitte einfach Ihre Hand.

Befragung

Entscheidungsblatt

Option A	Option B	Ihre Wahl
1/10 Chance auf €2.00; 9/10 Chance auf €1.60	1/10 Chance auf €3.85; 9/10 Chance auf €0.10	
2/10 Chance auf €2.00; 8/10 Chance auf €1.60	2/10 Chance auf €3.85; 8/10 Chance auf €0.10	
3/10 Chance auf €2.00; 7/10 Chance auf €1.60	3/10 Chance auf €3.85; 7/10 Chance auf €0.10	
4/10 Chance auf €2.00; 6/10 Chance auf €1.60	4/10 Chance auf €3.85; 6/10 Chance auf €0.10	
5/10 Chance auf €2.00; 5/10 Chance auf €1.60	5/10 Chance auf €3.85; 5/10 Chance auf €0.10	
6/10 Chance auf €2.00; 4/10 Chance auf €1.60	6/10 Chance auf €3.85; 4/10 Chance auf €0.10	
7/10 Chance auf €2.00; 3/10 Chance auf €1.60	7/10 Chance auf €3.85; 3/10 Chance auf €0.10	
8/10 Chance auf €2.00; 2/10 Chance auf €1.60	8/10 Chance auf €3.85; 2/10 Chance auf €0.10	
9/10 Chance auf €2.00; 1/10 Chance auf €1.60	9/10 Chance auf €3.85; 1/10 Chance auf €0.10	
10/10 Chance auf €2.00; 0/10 Chance auf €1.60	10/10 Chance auf €3.85; 0/10 Chance auf €0.10	

Befragung

Fragebogen 4

Wir möchten Ihnen gerne einige Fragen zu Ihren Gefühlen stellen. Uns interessiert, wie Sie Ihre Gefühle unter Kontrolle halten, bzw. regulieren. Zwei Aspekte Ihrer Gefühle interessieren uns dabei besonders. Einerseits ist dies Ihr emotionales Erleben, also was Sie *innen* fühlen. Andererseits geht es um den emotionalen Ausdruck, also wie Sie Ihre Gefühle verbal, gestisch oder im Verhalten nach *außen* zeigen. Obwohl manche der Fragen ziemlich ähnlich klingeln, unterscheiden sie sich in wesentlichen Punkten. Bitte beantworten Sie die Fragen, indem Sie folgende Antwortmöglichkeiten benutzen.

1--------------2--------------3--------------4--------------5--------------6--------------7

stimmt überhaupt nicht	neutral	stimmt vollkommen

1. ______ Wenn ich *mehr positive* Gefühle (wie Freude oder Heiterkeit) empfinden möchte, ändere ich, woran ich denke.
2. ______ Ich behalte meine Gefühle für mich.
3. ______ Wenn ich *weniger negative* Gefühle (wie Traurigkeit oder Ärger) empfinden möchte, ändere ich, woran ich denke.
4. ______ Wenn ich *positive* Gefühle empfinde, bemühe ich mich, sie *nicht* nach außen zu zeigen.
5. ______ Wenn ich in eine stressige Situation gerate, ändere ich meine Gedanken über die Situation so, dass es mich beruhigt.
6. ______ Ich halte meine Gefühle unter Kontrolle, indem ich sie *nicht* nach außen zeige.
7. ______ Wenn ich *mehr positive* Gefühle empfinden möchte, versuche ich über die Situation anders zu denken.
8. ______ Ich halte meine Gefühle unter Kontrolle, indem ich über meine aktuelle Situation anders nachdenke.
9. ______ Wenn ich *negative* Gefühle empfinde, sorge ich dafür, sie *nicht* nach außen zu zeigen.
10. _____ Wenn ich *weniger negative* Gefühle empfinden möchte, versuche ich über die Situation anders zu denken.

Anleitung

Willkommen zum Experiment! In diesem Experiment können Sie **bares Geld** verdienen. Wie viel Sie verdienen, hängt sowohl von Ihren Entscheidungen, als auch von den Entscheidungen der anderen Teilnehmer ab. Bitte lesen Sie diese Anleitung sorgfältig durch. Falls Sie Fragen zum Experiment haben, geben Sie bitte dem Experimentleiter ein Handzeichen.

Der Spielaufbau

Ihnen wird eine Symbolfolge bestehend aus 5 unterschiedlichen Symbolen angezeigt. Ihre Aufgabe ist es, diese in einer Menge von 20 Symbolfolgen wieder zu erkennen und anzuklicken. Nur eine einzige der 20 Symbolfolgen stimmt mit der gezeigten überein. Für jede Auswahl haben Sie maximal 7 Sekunden Zeit. Ist Ihre Antwort richtig, erhalten Sie eine positive Punktzahl auf Ihr Gesamtpunktekonto. Es wird nun automatisch eine neue Symbolfolge mit zugehörigen Lösungsvorschlägen angezeigt, aus denen Sie die identische Symbolfolge auswählen sollen. Ist Ihre Antwort falsch, erhalten Sie eine negative Punktzahl auf ihr Gesamtpunktekonto. Gleichzeitig wird die richtige Lösung angezeigt. Sollten Sie in den 7 Sekunden keine Antwort geben, bleibt Ihr Punktekonto unverändert und die nächste Symbolfolge wird automatisch angezeigt. Dieser Prozess widerholt sich solange, bis die rückwärtslaufende Zeit im Feld „Time left“ abgelaufen ist. Dann ist eine Runde des Spiels beendet. Ziel des Spiels ist es, in der vorgegebenen Zeit so viele richtige Antworten wie möglich zu geben.

Ablauf des Experiments

In diesem Experiment spielen Sie verschiedene Modi des Spiels für eine gewisse Zeitdauer. Zunächst beginnen Sie mit dem **Übungsmodus**. Während der Dauer von 1 Minute können sie das Spiel kennenlernen. Sie erhalten hierbei für jede richtige Antwort **+10 Punkte** auf das Gesamtpunktekonto und **-10 Punkte** für jede falsche Antwort. Anschließend spielen Sie den **Einzelmodus (Individual Mode)**. Dieser Modus dauert 5 Minuten lang. Ein richtige Antwort bringt **+10 Punkte**, eine falsche Antwort **-10 Punkte**. In diesem Modus hängt Ihr erzielter Gesamtpunktestand einzig von Ihrer eigenen Leistung ab. Anschließend spielen Sie den Teammodus und den Wettbewerb-Modus für jeweils 5 Minuten. Welchen der beiden Modi Sie zuerst spielen, wird zufällig bestimmt.

Im **Teammodus (Cooperative Mode)** bekommen Sie einen Mitspieler zugelost, **mit** dem Sie zusammenspielen. Ihre Aufgabe ist genau wie im Einzelmodus – übereinstimmende Symbolfolgen zu finden. Die Punktevergabe gestaltet sich nun so, dass Sie für eine eigene richtige Antwort **+5 Punkte** erhalten. Für eine falsche eigene Antwort erhalten Sie **-5 Punkte.** Zusätzlich werden Ihnen **5 Punkte** für eine richtige Antwort Ihres Mitspielers **gutgeschrieben** oder **5 Punkte** für eine falsche Antwort des Mitspielers **abgezogen**. Sie können in einer Tabelle am rechten Rand des Bildschirms sehen, ob die letzten 10 gegebenen Antworten von Ihnen und Ihrem Mitspieler richtig oder falsch waren und was dies für eine Auswirkung auf Ihr Punktekonto hat. In diesem Modus hängt Ihr erzielter Gesamtpunktestand zu gleichen Teilen von Ihrer eigenen Leistung und von der Leistung Ihres Mitspielers ab.

Im **Wettbewerbsmodus (Competitive Mode)** bekommen Sie einen neuen Spieler zugelost, **gegen** den Sie nun spielen. Die Punktevergabe gestaltet sich in diesem Modus so, dass Sie **+15 Punkte** für eine eigene richtige Antwort und **-15 Punkte** für eine eigene falsche Antwort erhalten. Zusätzlich werden Ihnen **5 Punkte** für eine richtige Antwort des Gegenspielers **abgezogen** und **5 Punkte** für eine falsche Antwort des Gegenspielers **gutgeschrieben**. Sie können in einer Tabelle am rechten Rand des Bildschirms sehen, ob die letzten 10 gegebenen Antworten von Ihnen und Ihrem Gegenspieler richtig oder falsch waren und was dies für eine Auswirkung auf Ihr Punktekonto hat. In diesem Modus hängt Ihr erzielter Gesamtpunktestand sowohl von Ihrer eigenen Leistung als auch der Leistung Ihres Gegenspielers ab.

Auszahlung

Jeder erzielte Punkt hat für Sie einen Wert von 1,3 Cent. Um Ihre Auszahlung zu bestimmen, werden alle von Ihnen erzielten Punkte aus den 3 Spielmodi aufsummiert Der resultierende Betrag wird Ihnen am Ende des Experiments ausbezahlt.

Beispiel

Um das Schema des Spiels zu veranschaulichen, zeigen wir Ihnen hier einen exemplarischen Auszug aus der Benutzeroberfläche, wie diese auf dem Bildschirm vor Ihnen während des Experiments zu sehen sein wird.

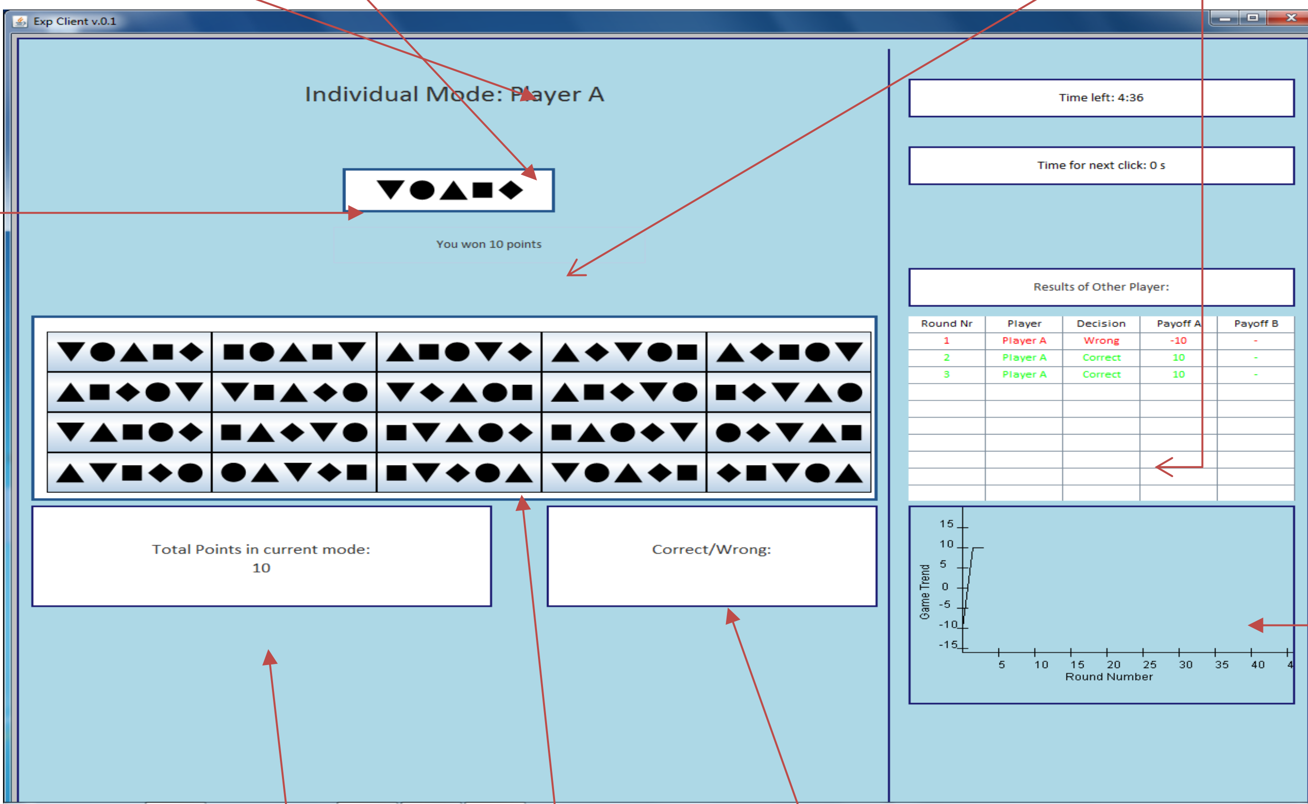
1. Der **Modus** indem Sie sich gerade befinden. Es gibt einen Einzelmodus, einen Teammodus und einen Wettbewerbsmodus.

2. Verbleibende **Zeit** bis zum Ende eines Spielmodus. Die Zeit läuft rückwärts von 5:00 Minuten bis 0:00

3. Verbleibende **Zeit** um zu klicken. Die Zeit läuft rückwärts von 7 Sekunden bis 0 Sekunden.

4. Die letzten 10 Antworten Ihres Mit- oder Gegenspielers. Zusätzlich wird angezeigt, welche Auswirkung die Antwort auf Ihren Gesamtpunktestand hat.

5. Anzeige von Punktgewinn oder Punktverlust



10. **Symbolfolge**, die Sie identifizieren sollen.

9. Aktueller **Gesamtpunktestand**. Beginnt in jedem Modus **bei 0 Punkten**.

8. Menge der **Antwortmöglichkeiten**, aus der Sie die übereinstimmende Symbolfolge durch Klicken auswählen

7. Anzeige ob, Ihre Wahl **richtig** oder **falsch** war.

6. **Graphische Veranschaulichung** der eigenen und anderen Antworten .

Schlussbemerkungen

Gerne beantworten wir Ihnen alle Fragen in Bezug auf diese Anleitung. Je besser Sie die Anleitung verstanden haben, desto mehr Geld können sie verdienen. Fragen zu Strategien können selbstverständlich nicht beantwortet werden.

Bevor das Experiment beginnt, wird eine Ruhephase von 5 Minuten stattfinden. Anschließend werden Ihnen an Ihrem Bildschirm zunächst einige Verständnisfragen zu den Regeln dieses Experiments gestellt. Geben Sie bitte die jeweiligen Antworten an Ihrem Computer ein. Im Anschluss daran findet eine Übungseinheit des Spiels wie oben beschrieben statt. Danach startet das eigentliche Experiment.

EEG ist eine Methode der medizinischen Diagnostik und der neurologischen Forschung zur Messung der elektrischen Aktivität des Gehirns durch Aufzeichnung der Spannungsschwankungen an der Kopfoberfläche. Es ist eine etablierte Untersuchungsmethode in der Neurologie. Die EEG-Messungen in unserem Experiment werden zur Aufzeichnung der Gehirnaktivität der Teilnehmer verwendet. Die Sammlung der Daten ist durch eine mit Elektroden bestückte Mütze realisiert, die auf dem Kopf des Teilnehmers getragen wird. Nach Befestigung der Mütze wird harmloses Anschlussfähigkeitsgel in die Elektrode eingefüllt, um die Leitfähigkeit zur Kopfhaut zu verbessern.

Die EEG Aufzeichnung ist sehr störungsanfällig, da Daten leicht von externen Störquellen beeinflusst werden können, wie beispielsweise Lärm oder unnötige muskuläre Bewegungen. Daher bitten wir Sie, möglichst alle unnötigen Bewegungen während des Experiments zu vermeiden.

Sollten Sie während des Experiments ergänzende Fragen haben, dann bleiben Sie bitte ruhig an Ihrem Platz sitzen und geben Sie dem Experimentleiter durch Handzeichen ein Signal. Warten Sie bitte, bis der Experimentleiter an Ihrem Platz ist, und stellen Sie dann Ihre Frage so leise wie möglich. Bleiben Sie bitte auch nach Ende des Experiments an Ihrem Platz und warten Sie auf weitere Anweisung der Experimentleitung. Sie können sich während des Experiments gerne Notizen auf dem bereitliegenden Notizblock machen. Die Teilnehmeranleitung sowie der Notizblock bleiben nach dem Experiment an Ihrem Platz zurück.

Bitte geben Sie hier Ihre Teilnehmer-Identifikation an:

Befragung

Fragebogen 1

Wie alt sind Sie?

__________ Jahre

Sind Sie

- ☐ männlich
- ☐ weiblich

Studieren Sie ein Fach mit wirtschaftswissenschaftlicher Ausrichtung?

- ☐ ja
- ☐ nein

Haben Sie schon einmal an Experimenten mit physiologischen Messungen teilgenommen?

- ☐ ja
- ☐ nein

Welcher Spielmodus hat Ihnen am besten gefallen?

- ☐ Einzelmodus
- ☐ Teammodus
- ☐ Wettbewerbsmodus

Hat die physiologische Messung während des Experiments dich gestört?

1---------2---------3---------4---------5

überhaupt nicht sehr stark

Hat die physiologische Messung an der anderen Person während des Experiments dich gestört?

1---------2---------3---------4---------5

überhaupt nicht sehr stark

Bitte beschreiben Sie Gedanken und Gefühle zu den eben durchgeführten Spielen:

Allgemein

Fragebogen 2

Wir möchten Ihnen gerne einige Fragen zu Ihren Gefühlen stellen, die Sie nach der Teilnahme an dem eben durchgeführten Spiel empfinden. Bitte beantworten Sie die Fragen, indem Sie folgende Antwortmöglichkeiten benutzen.

1---------2---------3---------4---------5---------6---------7---------8---------9---------10---------11

überhaupt nicht **neutral** **sehr stark**

	Einzelmodus	**Teammodus**	**Wettbewerbsmodus**
Aktiv/Rege (Active)	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11
Erregt/ Aufgeregt (Aroused)	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11
Nervös (Nervous)	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11
Überrascht (Surprised)	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11
Erregt/ Begeistert (Excited)	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11
Gelassen (Calm)	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11
Schläfrig (Sleepy)	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11	1 2 3 4 5 6 7 8 9 10 11

Fragebogen 3

Stellen Sie sich folgendes „Kopf oder Zahl“-Spiel vor:

Sie spielen mit mir eine „50/50-Lotterie“ bei der Sie 10 € verlieren können. (Das wäre Ihr Einsatz)
Was wäre der kleinste mögliche Gewinn, der diese Wette für Sie attraktiv macht?
(Das entspräche meinem Einsatz)

Zum Verständnis:

Ihr Einsatz würde bei diesem Kopf-oder-Zahl-Spiel 10€ betragen. Welchen Betrag müsste ich Ihnen als Gegenleistung anbieten, den Sie von mir gewinnen können, damit Sie dieses Spiel mit mir spielen? (Die Münze wird nur ein einziges Mal geworfen; Gewinnwahrscheinlichkeit 50% / 50%)

Bitte geben Sie den von Ihnen gewählten Betrag in das freie Feld ein.

Nun spielen wir dasselbe Spiel mit veränderten Bedingungen:

Die Münze wird wieder nur einmal geworfen und die Gewinnwahrscheinlichkeit ist wieder 50% / 50%. Dieses Mal ist aber Ihr Einsatz höher und zwar 1.000 €. Wie hoch muss der mögliche Gewinn (also der Einsatz, den Sie von mir gewinnen können) mindestens sein, damit dieses Spiel für Sie attraktiv ist?

Bitte geben Sie den von Ihnen gewählten Betrag in das freie Feld ein. *

Fragebogen 4

Wir möchten Ihnen gerne einige Fragen zu Ihren Gefühlen stellen. Uns interessiert, wie Sie Ihre Gefühle unter Kontrolle halten, bzw. regulieren. Zwei Aspekte Ihrer Gefühle interessieren uns dabei besonders. Einerseits ist dies Ihr emotionales Erleben, also was Sie *innen* fühlen. Andererseits geht es um den emotionalen Ausdruck, also wie Sie Ihre Gefühle verbal, gestisch oder im Verhalten nach *außen* zeigen. Obwohl manche der Fragen ziemlich ähnlich klingen, unterscheiden sie sich in wesentlichen Punkten. Bitte beantworten Sie die Fragen, indem Sie folgende Antwortmöglichkeiten benutzen.

1--------------2--------------3--------------4--------------5--------------6--------------7

stimmt überhaupt nicht — **neutral** — **stimmt vollkommen**

1. ______ Wenn ich *mehr positive* Gefühle (wie Freude oder Heiterkeit) empfinden möchte, ändere ich, woran ich denke.
2. ______ Ich behalte meine Gefühle für mich.
3. ______ Wenn ich *weniger negative* Gefühle (wie Traurigkeit oder Ärger) empfinden möchte, ändere ich, woran ich denke.
4. ______ Wenn ich *positive* Gefühle empfinde, bemühe ich mich, sie *nicht* nach außen zu zeigen.
5. ______ Wenn ich in eine stressige Situation gerate, ändere ich meine Gedanken über die Situation so, dass es mich beruhigt.
6. ______ Ich halte meine Gefühle unter Kontrolle, indem ich sie *nicht* nach außen zeige.
7. ______ Wenn ich *mehr positive* Gefühle empfinden möchte, versuche ich über die Situation anders zu denken.
8. ______ Ich halte meine Gefühle unter Kontrolle, indem ich über meine aktuelle Situation anders nachdenke.
9. ______ Wenn ich *negative* Gefühle empfinde, sorge ich dafür, sie *nicht* nach außen zu zeigen.
10. _____ Wenn ich *weniger negative* Gefühle empfinden möchte, versuche ich über die Situation anders zu denken.

Fragebogen 5

Bitte geben Sie für jede der folgenden Aussagen an, in welchem Maße diese charakteristisch für Sie sind. Wenn eine Aussage extrem uncharakteristisch für Sie ist, schreiben Sie eine „1“ vor die Aussage. Ist eine Aussage sehr charakteristisch für Sie, schreiben Sie eine „5“ vor die Aussage. Bitte beantworten Sie die Aussagen, indem Sie folgende Antwortmöglichkeiten benutzen.

1--------------2--------------3--------------4--------------5

Sehr uncharakteristisch unsicher sehr charakteristisch

1. ______Ich ziehe komplexe Probleme einfachen vor.
2. ______Ich übernehme gerne die Verantwortung in Situationen, die viel Nachdenken erfordern.
3. ______Nachdenken macht mir keinen Spaß.
4. ______Ich würde lieber etwas tun, das nicht viel Nachdenken erfordert, anstatt etwas, das meine Denkfähigkeit herausfordert.
5. ______Ich versuche Situationen, in denen ich wahrscheinlich intensiv über etwas nachdenken muss, vorauszuahnen und zu vermeiden.
6. ______Ich finde es befriedigend, stunden lang intensive Überlegungen anzustellen.
7. ______Ich denke nur so intensive nach, wie ich muss.
8. ______Ich denke lieber über kleine, kurzfristige Projekte als über langfristige nach.
9. ______Ich mag Aufgaben, die wenig Nachdenken erfordern, wenn ich sie einmal gelernt habe.
10. ______Die Idee, mir mit meiner Intelligenz den Weg nach oben zu bahnen, gefällt mir.
11. ______Aufgaben, bei denen ich mir neue Lösungen für Probleme ausdenken muss, gefallen mir wirklich.
12. ______Neue Arten des Denkens zu lernen gefällt mir eigentlich nicht.
13. ______Ich finde es gut, wenn mein Leben voller Rätsel ist, die ich lösen muss.
14. ______Ich denke gerne abstrakt.
15. ______Ich würde eine Aufgabe, die intellektuell anspruchsvoll, schwierig und wichtig ist, einer vorziehen, die zwar wichtig ist, aber nicht viel Nachdenken erfordert.
16. ______Nach einer Aufgabe, die viel geistige Anstrengung erfordert hat, bin ich eher erleichtert als befriedigt.
17. ______Mir reicht es, wenn etwas funktioniert; mir ist es egal, wie oder warum es funktioniert.
18. ______Ich denke gewohnheitsmäßig auch über Probleme nach, die mich nicht persönlich betreffen.

Fragebogen 6

Warum sind Sie motiviert Ihre Arbeit zu erledigen?

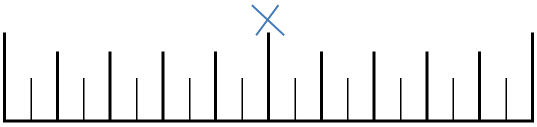
Bitte bewerten Sie die folgenden Aussagen auf einer Skala von 1 (überhaupt kein Zuspruch) bis 7 (starker Zuspruch).

1.______	Weil es mir wichtig ist, anderen mit meiner Arbeit zu nützen.
2.______	Weil ich die Arbeit selbst mag
3.______	Weil ich anderen durch meine Arbeit helfen möchte
4.______	Weil es Spaß macht
5.______	Weil ich positiven Einfluss auf andere nehmen möchte
6.______	Weil ich die Arbeit attraktiv finde
7.______	Weil es mir wichtig ist anderen durch meine Arbeit etwas Gutes zu tun
8.______	Weil ich es genieße

Fragebogen 7

Bitte schätzen Sie im Folgenden Ihre Beanspruchung während des Experiments ein.

Beispiel:

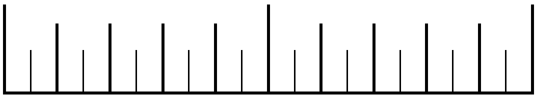


Gering Hoch

Wie viel geistige Anforderung war bei der Informationsaufnahme und bei der Informationsverarbeitung erforderlich

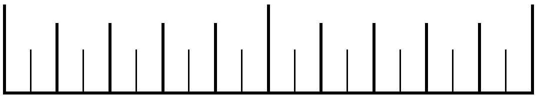
Geistige Anforderung

Einzelmodus



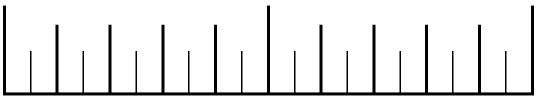
Gering Hoch

Teammodus



Gering Hoch

Wettbewerbsmodus

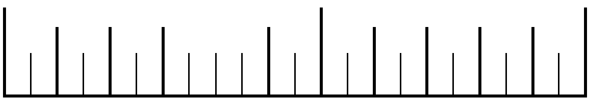


Gering Hoch

Wie viel Zeitdruck empfanden Sie hinsichtlich der Häufigkeit oder dem Takt mit dem die Aufgaben oder Aufgabenelemente auftraten?

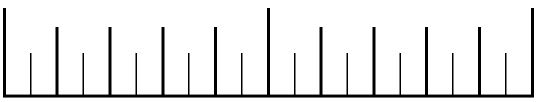
Zeitliche Anforderung

Einzelmodus



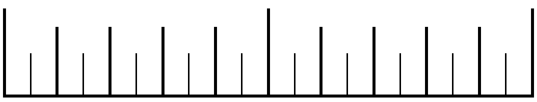
Gering Hoch

Teammodus



Gering Hoch

Wettbewerbsmodus



Gering Hoch

Wie erfolgreich haben Sie Ihrer Meinung nach die vom Versuchsleiter gesetzten Ziele erreicht?

Leistung

Einzelmodus

Gut Schlecht

Teammodus

Gut Schlecht

Wettbewerbsmodus

Gut Schlecht

Wie hart mussten Sie arbeiten, um Ihren Grad an Aufgabenerfüllung zu erreichen?

Anstrengung

Einzelmodus

Gering Hoch

Teammodus

Gering Hoch

Wettbewerbsmodus

Gering Hoch

Wie frustriert fühlten Sie sich während der Aufgabe?

Frustration

Einzelmodus

Gering Hoch

Teammodus

Gering Hoch

Wettbewerbmodus

Gering Hoch

Bitte vergleichen Sie im Folgenden zeilenweise die einzelnen Dimensionen Ihrer Beanspruchung und geben Sie **für jedes Paar** an, welche Dimension jeweils die größere Rolle gespielt hat (ein Kreuz pro Zeile).

Einzelmodus

	Auswahl		
Zeitliche Anforderung			Geistige Anforderung
Leistung			Geistige Anforderung
Zeitliche Anforderung			Anstrengung
Leistung			Zeitliche Anforderung
Frustration			Geistige Anforderung
Anstrengung			Leistung
Zeitliche Anforderung			Frustration
Geistige Anforderung			Anstrengung
Leistung			Frustration
Frustration			Anstrengung

Teammodus

	Auswahl		
Zeitliche Anforderung			Geistige Anforderung
Leistung			Geistige Anforderung
Zeitliche Anforderung			Anstrengung
Leistung			Zeitliche Anforderung
Frustration			Geistige Anforderung
Anstrengung			Leistung
Zeitliche Anforderung			Frustration
Geistige Anforderung			Anstrengung
Leistung			Frustration
Frustration			Anstrengung

Wettbewerbsmodus

	Auswahl		
Zeitliche Anforderung			Geistige Anforderung
Leistung			Geistige Anforderung
Zeitliche Anforderung			Anstrengung
Leistung			Zeitliche Anforderung
Frustration			Geistige Anforderung
Anstrengung			Leistung
Zeitliche Anforderung			Frustration
Geistige Anforderung			Anstrengung
Leistung			Frustration
Frustration			Anstrengung

Appendix C

Arousal-Workload additional findings

Detailed Procedure for emotional arousal from Measured Heart Rates

To operationalize emotional arousal (EA), heart rates of all participants were measured before the experiment (baseline heart rate) and also before each bid. In order to make heart rates comparable across participants, we normalized the heart rates prior to the bid by dividing each value by a participant's baseline heart rate. For each participant and auction, this yields 20 normalized heart rate values, in the time interval of 3 to 1 seconds directly prior to the bid (in slots of .1 second each). EA of a bid was calculated by reducing the 20 normalized heart rate values to a single factor using Principal Component Analysis with promax rotation (Shivappa et al., 2010). The last second before bid submission (E2) is not included in the computation of the factor, since this period typically constitutes the preparation of the imminent bidding action (Teubner et al., 2015). The PCA yields a standardized variable with mean 0 and standard deviation 1 for each combination of participant and auction, as shown in Table 1. The actual statistics of EA do not exactly match 0 and 1, generated by the PCA process. The mean value is –.022, standard deviation is .98. The small aberration stems from the fact that, while combining the dataset of heart rate measures with EEG, some observations had to be dropped due to EEG measurement errors.

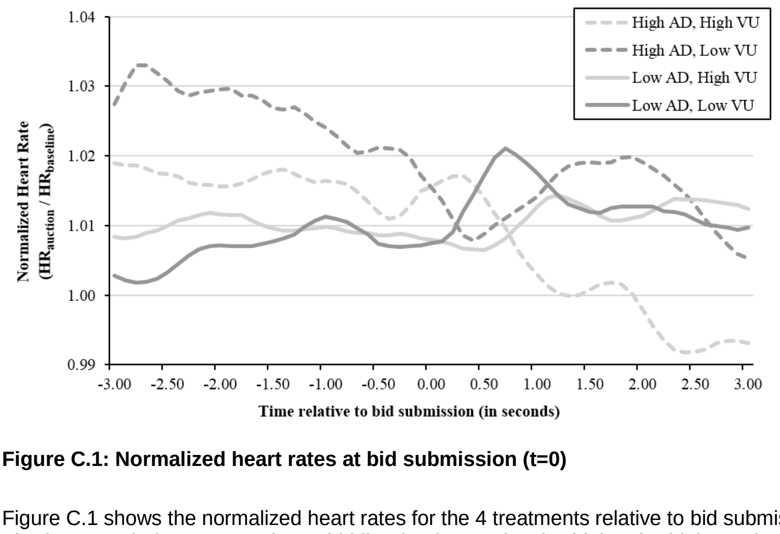


Figure C.1: Normalized heart rates at bid submission (t=0)

Figure C.1 shows the normalized heart rates for the 4 treatments relative to bid submission (E2). The increase in heart rate prior to bidding is observed to be higher for high auction dynamics (Dutch auctions) than low auction dynamics (FPSB auctions), whereas the differences for different levels of value uncertainty are less pronounced.

Detailed Procedure for Computing Cognitive Workload from Measured EEG Activity

We followed the procedure of Pope et al. (1995). The EEG data was sampled at 500 Hz with a bandpass filter from 1 Hz to 40 Hz. The computation of cognitive workload index was executed in two steps: (1) Computation of independent components and (2) Computation of spectral powers in the above frequency bands. Independent components were computed using fast Independent Component Analysis (fastICA) algorithm available in the EEGLab toolbox for 14 frontal channels for each subject, and a Matlab script was developed to automate the process across all participants. Correspondingly, 14 independent components resulted, which were artefact cleaned for each subject by eyeball inspection, to remove components with possible eye, muscle movements or electrical interference. Next, power spectra were calculated for 2 second windows before each event, across each treatment type for 6 events of interest during the auction as shown in Figure 3. The EEG cognitive workload index mirrors the theoretical definition of cognitive workload, taking into account the absolute and relative power spectra from 1 to 30 Hz of EEG channel. The spectral powers of each of the frequency bands (Beta, Alpha, and Theta) are calculated on the independent components obtained from 14 frontal channels, and then cognitive workload is computed by the formula (Beta / (Alpha + Theta)) spectral power (Pope et al., 1995).

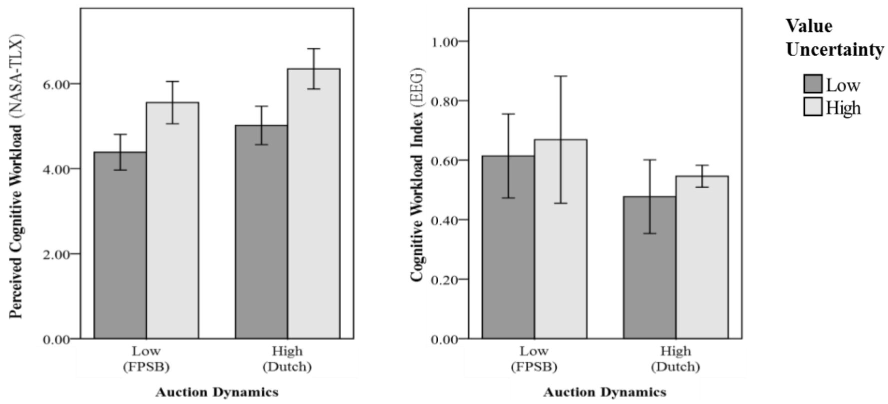


Figure C.2: 1) Perceived cognitive workload (NASA-TLX), 2) Cognitive workload index (EEG)

Figure C.2 shows that both perceived and measured cognitive workload indices were higher for high than for low value uncertainty auctions. The dimension of physical demand has been omitted from the NASA TLX, since it is not relevant for the sedentary auction task. PCW was higher for Dutch than for FPSB auction, CW was higher for FPSB than Dutch auctions. However, the difference in means is only marginal, and not significant.

Table C.1. Auction dynamics (AD) and value uncertainty (VU) moderating the influence of emotional arousal (EA) on deviations from RNNE strategy

	Dependent Variable: Bidding Behavior (ΔRNNE [MU])		
	B (SE)		B (SE)
EA	-.267 (.239)		
Dummy: AD	-.066 (.493)		-.508 (3.137)
Dummy: VU	4.882 (.310)	***	1.427 (1.592)
EA x High AD	-.018 (.460)		
EA × High VU	-.010 (.319)		
High AD x High VU	1.661 (.662)	*	-.450 (4.017)
High AD x High VU x EA	1.448 (.668)	*	
CW			-1.998 (2.416)
CW × High AD			.580 (5.924)
CW × High VU			6.366* (2.872)
High AD x High VU x CW			4.322 (7.535)
Dummy: Risk averse	.661 (1.285)		
Round	-.028 (.012)	*	-.023* (.012)
Constant	2.056 (1.227)	***	3.021 (1.853)
R^2within (R^2overall)	.328(.236)		.326(.238)

N=878, Number of subjects = 37. 2 subjects were removed due to incomplete data points. Number of possible cases = 20(FPSB)* 37 (subjects) + 20 (Dutch) * 37 (subjects)* (1/3) = 986, since participants are expected to win 1/3rd of the auction cases. Auctions where participants did not click (and hence lost) were not considered in the computation of RNNE deviations. H1a-H2b are based on GLS regressions with subject random effects. Regression coefficients with standard errors in parentheses. + *p*<.1; * *p*<.05; ** *p*<.01; *** *p*<.001

Appendix D

Interaction and group models for serious games performance

Table D.1: Logistic Regression Results for Group Game Performance

	Dependent Variable	
Independent Variable	Payoff Coop	Payoff Comp
Gender: Female	.496(.205)*	.174(.116)
Reappraiser score	.214(.027)***	.058(.015)***
Suppressor score	-.091(.026)***	-.120(.015)***
Need for cognition	-.011(.003)***	.009(.001)***
Gender x Reappraiser score	-.217(.035)***	-.161(.020)***
Gender x Suppressor score	.030(.033)	.088(.019)***
Gender x Need for cognition score	.001(.004)	.007(.002)***
Treatment Order	.121(.010)***	.133(.014)***
Constant	-.240(.176)	-.021(.098)

Note: + p<.1; * p<.05; ** p<.01; *** p<.001. N= 293 (156 participants*2 game modes =312, 19 data points were removed due to incomplete data in one or more of the questionnaires). Scores of reappraisal, suppression, and need for cognition included the scale of 0.

Table D.2: Moderated Mediation Analysis for Game Performance

Hypothesis		*Dependent Variable* Hits		Misses		Unclicked	
		Estimate (Confidence Interval)					
H3: Emotion Regulation moderates the mediating impact of emotion on game performance (Reappraiser = 4.5)	Direct effects	-1.141 (-2.435,0.203)	*	0.537 (0.110,0.975)	*	0.587 (-.622,1.826)	
	Indirect Effects	0.280 (0.036,0.624)	*	0.361 (-.091,0.846)	*	-.094 (-.336,0.083)	
	Total Effects	-.861 (-2.143,0.523)		0.361 (-.091,0.846)		0.488 (-.735,1.732)	
	Prop. Mediated	-0.236 (-5.262,2.769)		-.428 (-6.784,4.163)		-.083 (-1.956,2.608)	
H4: Need for cognition moderates the mediating impact of cognitive workload on game performance (NCS=20)	Direct effects	-.442 (-1.795,0.980)		0.249 (-.223,0.756)		0.191 (-1.118,1.485)	
	Indirect Effects	-.951 (-1.813,-.244)	**	0.343 (0.087,0.667)	**	0.592 (0.032,1.315)	*
	Total Effects	-1.392 (-2.843,0.202)	*	0.593 (0.064,1.151)	*	0.782 (-.543, 2.127)	
	Prop. Mediated	0.628 (-1.543,3.699)	*	0.574 (1.135,2.553)	*	0.591 (-3.663,5.069)	

Table D.3: Impact of different aggregation methods on group payoff in cooperative and competitive modes

	Dependent Variable	
	Coop Payoff #Difference	Comp Payoff #Average
Dummy: Female	-0.360(0.025)***	-0.349(0.029)***
Excited (emotion)	-0.087(0.016)***	-0.166(0.008)***
Active (emotion)	0.024(0.008)**	0.061(0.009)***
Cognitive workload	0.024(0.008)**	0.021(0.005)***
Reappraiser	-0.098(0.028)***	-0.047(0.017)**
Suppressor	0.461(0.030)***	0.033(0.017)*
Need for cognition	-0.027(0.003)***	-0.033(0.002)***
Dummy: Treatment order	0.036(0.025)	0.143(0.026)***
Constant	0.328 (0.052)***	2.346(0.160)***
Hosmer and Lameshow R^2	0.238	0.228

Figure D.1 depicts the heatmap of experienced workload, whenever the target pattern was in position n, where n is from 1 to 20 possible positions. It can be seen, that there were not major differences in the experienced workload due to the position of the pattern. This was true, for both cooperative and competitive modes, and for all performance measures. Participants experienced the highest workload in position 2, on the top row, second column. Thus, it is likely that these patterns were harder to find, due to their position. However, this was not significantly predicting performance, when tested with a regression as well.

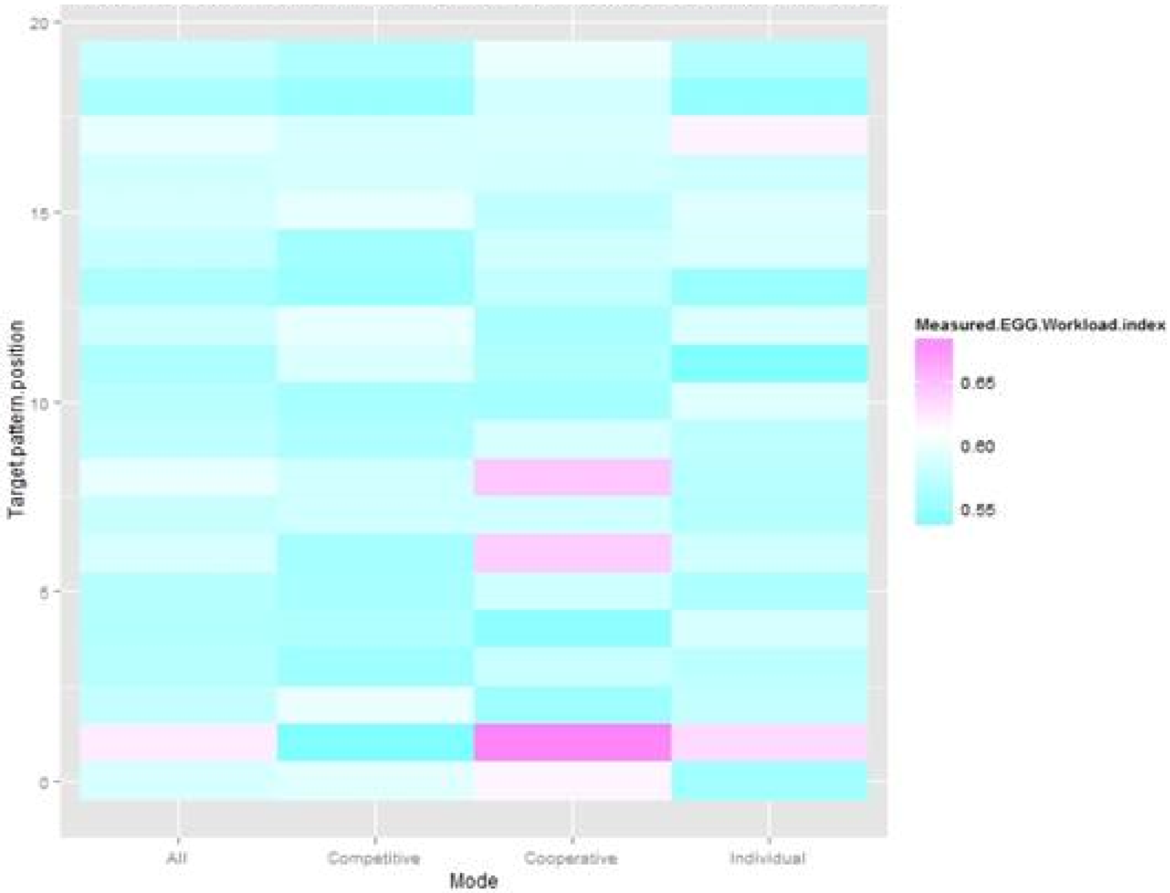


FIGURE D.1: *Heatmap depicting experienced workload, in each of the positions 1-20*

Figure D.2 depicts the workload for each of the 42 rounds. As can be observed, the workload tends to remain predominantly stable, with a tendency for lower workload towards the end of the game, only in the case of individual mode. Hence, it may be concluded that, in the context of game play, especially in cooperative and competitive modes, workload tends to remain relatively stable. In other words, participants were required to expend continuous effort in scoring well across the experiment.

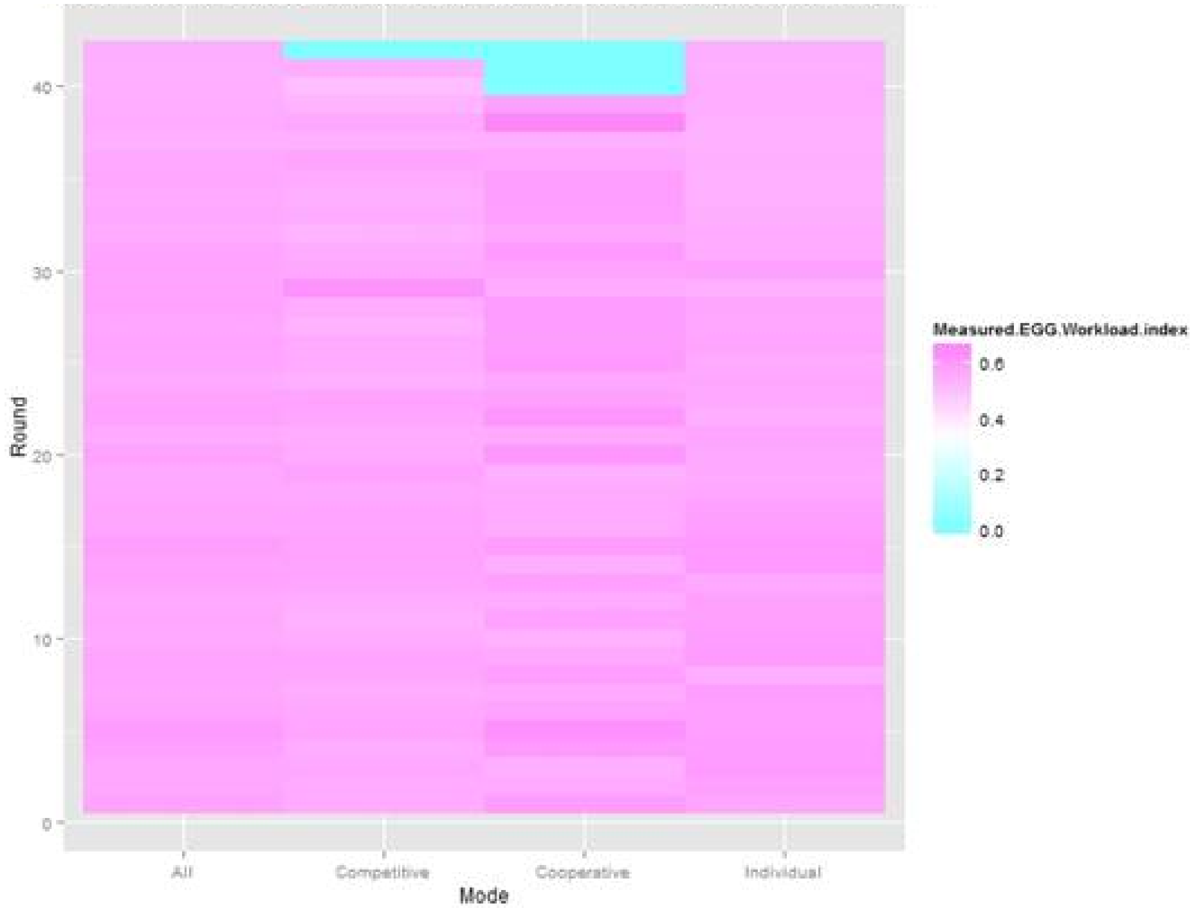


FIGURE D.2: *Heatmap depicting experienced workload, in each round of game play*

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List of Abbreviations

AAPB	**A**ssociation for **A**pplied **P**sychophysiology and **B**iofeedback
AD	**A**uction **D**ynamics
AR	**AR**ousal
BART	**B**alloon **A**nalogue **R**isk **T**ask
BOLD	**B**lood **O**xygenation **L**evel **D**ependent
Brownie	**B**ehavioral **R**esearch of gr**O**ups using **W**eb and **N**euroIS **E**xperiments
DAO	**D**ata **A**ccess **O**bject
CART	**C**lassification **a**nd **R**egression **T**rees
CW	**C**ognitive **W**orkload
ECG	**E**lectro**c**ardio**g**raphy
EDA	**E**lectro**d**ermal **a**ctivity
EEG	**E**lectro**e**ncephalo**g**raphy
EMG	**E**lectro**m**yo**g**raphy
ER	**E**motion **R**egulation
ERQ	**E**motion **R**egulation **Q**uestionnaire
EUT	**E**xpected **U**tility **T**heory
EV	**E**xpected **V**alue
fMRI	**f**unctional **M**agnetic **R**esonance **I**maging
FPSB	**F**irst **P**rice **S**ealed **B**id
HFLF	**H**igh **F**requency **L**ow **F**requency
HR	**H**eart **R**ate
HRV	**H**eart **R**ate **V**ariability
IADS	**I**nternational **A**ffective **D**igital **S**ounds
IAPS	**I**nternational **A**ffective **P**icture **S**ystems
IM	**I**ntrinsic **M**otivation
LBF	**L**ive **B**io-**f**eedback
MU	**M**onetary **U**nits
NASA-TLX	**N**ational **A**eronautics and **S**pace **A**dministration **T**ask **L**oad **I**ndex
NCS	**N**eed for **C**ognition **S**cale
NeuroIS	**N**euro **I**nformation **S**ystems
NIRS	**N**ear **I**nfra- **R**ed **S**pectroscopy
OLS	**O**rdinary **L**east **S**quares
PC	**P**rincipal **C**omponent
PCA	**P**rincipal **C**omponent **A**nalysis
PET	**P**ositron **E**mission **T**omography
PPG	**P**hoto**p**lethysmo**g**ram

PSM	**P**ro**s**ocial **M**otivation
RNNE	**R**isk **N**eutral **N**ash **E**quilibrium
SCR	**S**kin **C**onductance **R**esponse
SPR	**S**ociety for **P**sychological **R**esearch
UI	**U**ser **I**nterface
VU	**V**alue **U**ncertainty

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List of Symbols

€	Euro
x	Private signal shown to the bidder
ϵ	Uncertainty in drawing the private signal from the true value
$\underline{x}$	Lower bound of true value of the good
$\overline{x}$	Upper bound of true value of the good
$\gamma(x)$	Risk-neutral Nash Equilibrium function
$\Delta RNNE$	Deviation from benchmark Risk-neutral Nash Equilibrium bid

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