Emotions and Emotion Regulation in Economic Decision Making

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Chapter 1.

Motivation and Introduction

1.1. Influence of Emotions and Emotion Regulation on Decision Making

Individuals systematically deviate from theoretic predictions when coming to economic decisions, and frequently these deviations are explained by the influencing role of emotions (Kuhnen and Knutson, 2005). In fact, there is a broad account of experimental and field studies which demonstrate that emotional states of high arousal can become unmanagable, adversely affecting decision makers (e.g. Ku et al., 2005; Lo et al., 2005). Already since the middle of the 20th century it became evident that the neo-classical, purely consequentialist economic perspective struggles with a lot of empirical findings. Consequently, the characterization of humans' behavior according to the always rational *homo economicus* is probably now discussed more controversial than ever before.

With the advent of behavioral economics, economists' perspective broadened and began to incorporate aspects from the field of cognitive psychology. Concepts such as *bounded rationality* helped to widen the picture and to raise awareness that human cognition is intertwined with decision processes, and may also be a limiting factor (Kahneman, 2003; Rabin, 1998). Complementary, also the influence of emotions on cognition, risk taking and decision making was recognized (Loewenstein et al., 2001; Loewenstein and Lerner, 2003). Thereby, economic literature has typically regarded emotions as the opposite of rationality and hence focused on its negative effects, such as biasing one's original preferences, skewing one's information retrieval and eventually shifting one's decision making behavior. And the explanatory power of emotions seems manifold as economists suspect emotions to be the underlying driving force of a whole set of decision biases such as the *disposition effect*[1], loss and regret aversion, or the phenomenon of auction fever (Shefrin and Statman, 1985; Sokol-Hessner et al., 2008; Engelbrecht-Wiggans and Katok, 2008; Ku et al., 2005). Whereas emotions certainly *can* have these drawbacks on decision processes, theories bolstered by findings from economic psychology and psychophysiology, have also recognized another, beneficial side of emotions for individual decision making. Isen (2001) argued that "positive affect" can be a primary source for creative problem solving, cognitive processing and decision making under complex or stressful situations. Bechara and Damasio (2005) argued that adequate emotional processing is a necessary prerequisite for fast and advantageous decision making. In summary, literature gives an account for both the beneficial but also the maladaptive effects of emotions, in fact often dependent on the context the decision maker faces. These Janus-faced qualities of emotions need to be integrated in a more expanded conception: maybe, asking whether an emotion is beneficial or maladaptive for decision making *per se* is the wrong question (Fenton-O'Creevy et al., 2011).

Seo and Barrett (2007, p. 923) observed in a study involving traders that subjects, which "were better able to identify and distinguish among their current feelings achieved higher decision performance." The authors concluded that "emotion differentiation and affective influence regulation are two essential process components of emotional intelligence" which improve individual decision performance (Seo and Barrett, 2007, p. 934). Similarly, Fenton-O'Creevy et al. (2011), among others (e.g. Heilman et al., 2010), followed this conjecture: emotions should not be considered as always target-oriented or disruptive. Rather, the ability to understand one's emotions when they set in, and to regulate them accordingly when necessary seems essential for beneficial decision making. The construct of influence regulation traces back to the psychological concept of *emotion regulation*, which has gained considerable attention in recent years (Gross, 2009). According to Gross (1998b) an emotion is not merely passively experienced, but it unfolds along an emotion generation process and humans have continuously the opportunity to interfer with this unfolding process. Essentially, the way we regulate our emotions largely reflects how we experience them and therefore react upon them. According to the concept of emotion regulation, subjects regulate emotional stimuli

[1]The disposition effect is defined by Shefrin and Statman (1985) as an investor's tendency to sell winning stocks too early, while riding losing stocks too long. This effect can be observed in many empirical stock data sets.

by applying specific regulation strategies, e.g., reappraisal or suppression (Gross and John, 2003). For instance, one may or may not down-regulate a burgeoning timidity during a bumpy flight. Suppression of this timidity could unfold in one experiencing high fear of a plane crash, but not expressing this fear. Reappraisal on the other hand might result in becoming aware that for the pilot a bumpy flight might be nothing else than corrugations in the road surface for a car driver. Depending on the employed strategy and the intensity of the stimulus, a subject might or might not be successful in regulating a relevant or irrelevant stimulus. Emotion regulation manifests in experience, expression and physiology (Gross, 1998a). Some studies could already bring first insights into the question of whether emotion regulation also improves decision making in economic contexts (Heilman et al., 2010; Fenton-O'Creevy et al., 2012). It is a promising and exciting task to further disentangle the question of how emotion regulation and decision making are intertwined and how emotion regulation might improve our understanding of economic and financial decision making.

Occasions to actually experience emotions during economic and financial decision making in the real world are multifaceted—and has potentially increased in the last decades. Digitally enabled progress has fostered e-commerce since the 1990s, generating a variety of new market platforms. Electronic markets with their manifestations in electronic auctions or private online trading platforms have turned out to be highly successful. Alone in late 2012 the share of self-directed investors amounted to almost 59 per cent of all investors in Germany.[2] Especially participating in electronic auctions and trading involves states filled with high emotional arousal which can eventually result in financial losses (Adam et al., 2011; Lo and Repin, 2002; Fenton-O'Creevy et al., 2011). Platform operators' strategies to boost emotional reactions seem manifold: Countdowns induce time pressure in electronic auctions, switching their colour shortly before the good is finally auctioned off. Other auction platforms display images likely to trigger states of community or competition. In online market platforms, potential gains and losses are indicated with green and red arrows—on some trading floors market events or large transactions are even accompanied by the sound of roaring race cars. These emotional stimuli foster emotionality and individuals' market behavior. Also from a

[2] http://www.derivateverband.de/DE/MediaLibrary/Document/Studies/2012%2012%2018%20Steinbeis-Studie%20Selbstentscheider-Kunden%20im%20Wertpapiergesch%C3%A4ft.pdf (retrieved on 08/19/2013)

market-engineering perspective it is necessary to better understand how these often subliminal experienced events influence the users' decision making in such electronic markets (cf. Weinhardt et al., 2003).

While young private users are typically unaware of the coherence of the emotional state and their decision behavior, interestingly, professional traders and experienced private investors are meanwhile well aware of the coherence of emotions, emotion regulation and decision making (Fenton-O'Creevy et al., 2011). In their strive for profit, they do know about the emotions involved in trading and the importance of understanding the emotional state that evolves within the process. Trading platform operators such as the investment bank *SAXO Bank* have recognized this shift and meanwhile developed questionnaires and training sessions in order to provide their users with more knowledge about emotion regulation and improve their capabilities to "remain level-headed" in critical situations.[3] Consequently, also for research it seems highly relevant to enhance the theoretical understanding of how the concept of emotion regulation can contribute to improving financial decision making.

1.2. Advances in Biosensor Technology

Traditional experimental economic research struggles—invariably of the emotion competent stimulus—with the assessment of what a subject actually experiences. One major problem is that the measurement of emotions is difficult as self-reports can lack from certain shortcomings, such as subjects being dishonest, social desirability, or the time gap between the emotion experience and assessment may bias perception (Capra et al., 2010). For that reason, many models, that employ emotions for their underlying theory, are still hypothetical about the existence of emotions. And of course, a model can always only be as good as the underlying theory.

Typically, emotions manifest in perception and behavior but also in psychophysiological correlates, which were historically very slow and effortful to collect (Myers, 2004). The rapid progress in the field of data storage, treatment and biosensor-technology now offers the opportunity of fast and automated data acquisition and processing. Therefore the close-grained time-accurate evaluation of emotional states during large scale experimental sessions has the potential to significantly extend traditional research on the

[3]http://www.tradingfloor.com/topics/train-your-brain (retrieved on 08/19/2013)

coherence of formerly invisible processes such as emotions and emotion regulation with decision making. Moreover, the time-synchronous and continuous psychophysiological data assessment and processing meanwhile allows the development of so called NeuroIS tools (Vom Brocke et al., 2013). These tools can for instance employ biofeedback, i.e., the indication of one's own emotional state, and in turn utilize these usually unperceivable visceral processes to increase the decision makers awareness for her or his emotional state.

1.3. Working Hypothesis and Research Questions

Adam (2010) developed a structured method for disentangling the coherence of emotions, measured by physiological correlates such as heart rate or skin conductance, and economic decision making in auction experiments. The method offers the potential to answer many additional questions in fields were emotions affect our economic decision behavior. Auctions are particularly suitable for investigating these relationships since auction participants often experience states of strong arousal, and emotions experienced in this context are often blamed for being the cause of suboptimal decisions. In addition, auctions have a high economic relevance and are particularly well suited to systematically analyze economic decision making in laboratory experiments. Especially first-price sealed-bid auctions are useful in this context, since they allow to decouple the examination of integral emotions, i.e. triggered through the auction mechanism (e.g. winning and losing), and incidental emotions, i.e. not elicited by the auction mechanism (e.g. influence of affective images). However, up to now it is not clear how successful psychophysiology will prove in the pursuit to improve economic and Information Systems (IS) theory. This thesis aims to inform research about the interrelationship of emotions, emotion regulation and decisions by employing the potential and benefits of psychophysiology. Affirmative results would on the one hand strengthen the method as such in the domain of economics and IS, on the other hand help to inform theory—and therefore researchers' understanding—of how emotions in economic contexts are experienced and how they influence our decision making. Therefore, the underlying working hypothesis for the Chapters 2, 3 and 4 of this thesis is that the consideration of emotions and emotion regulation can help us in our ambition to understand individuals' economic decision making. Chapter 5 will extend this hypothesis towards the direction that emotional awareness and emotion regulation can be trained with the aim to actively improve economic decision making. Therefore the gap is bridged from using psychophysiology *ex post* as an explanatory tool towards the direction of how physiology (with its feature live biofeedback) can be applied in order to inform the users of electronic markets about their emotional state in real time and hence to improve emotional awareness during the decision process.

This thesis will approach the solution process by employing economic experiments whereas employing tools from NeuroIS in order to assess subjects' physiological states during their decision processes. Thereby a central idea is to elicit emotions by varying feedback information or images within or between the treatment designs. The interrelatedness of subjects' economic behavior, their emotions and emotion regulation strategies will then be studied and discussed. It will become clear that psychophysiology provides essential information regarding subjects' ongoing emotional states. Furthermore the concept of emotion regulation, which has not gained extensive consideration in economic and IS research so far, turns out to have exploratory power of subjects' underlying decision patterns. The results contribute to a deeper understanding of how emotion regulation strategies unfold physiologically and economically. Moreover, this thesis provides new insights of how live biofeedback can be employed in adaptive information systems in order to inform subjects about their emotional state and thereby aid their decision making.

As mentioned above, the first-price sealed-bid auction with its auction mechanism is suitable for the decipherment of indivuals' emotional states and their decision making, by employing psychophysiology. Constructs from economic and IS theory dealing with emotions in auctions therefore lay the foundation for the following research questions.

> **Research Question 1:** *Do bidders in first-price sealed-bid auctions experience regret, and if so, does regret influence bidders' decision making?*

Two forms of the emotion *regret* can be experienced in a first-price sealed-bid auction—*loser regret* and *winner regret*. On the one side, a bidder may suffer from loser regret when the auction is lost, whereas a higher bid could have resulted in a profitable outcome. Winner regret, on the other side, may be experienced when the bidder wins the auction, but a lower bid may have resulted in a higher profit. In their work Engelbrecht-Wiggans and Katok (2008) infer that the aversion to regret may be a major reason for "overbidding." However, the authors' explanation is hypothetical in nature and still little is known about subjects' actual experience and processing of the displayed regret information during electronic auctions. Employing methods from psychophysiology help to disentangle the coherence of bidders' cognitive processing, emotional experience and economic decision making, since it allows to objectively measure a subject's response to the regret feedback information within the auction process.

> **Research Question 2:** *Do "joy of winning" and "frustration of losing" in first-price sealed-bid auctions occur, and if so, which one is more prevalent?*

Research concerned with auction data frequently explains bidders' decision making as triggered by emotions such as "joy of winning" and "frustration of losing." The underlying debate yields the question which of the two emotional stimuli actually is the prominent one (Delgado et al., 2008). However, little is known regarding about whether subjects actually experience those emotional states during the auction process and whether winning or losing an auction is independent of the potential profit that could have been realized within the auction. Psychophysiology provides an opportunity to assess the emotional intensity and valence related to the revealed auction outcome and therefore to differentiate these distinct emotional patterns.

> **Research Question 3:** *What is the impact of incidental social images in first-price sealed-bid auctions on emotions, emotion regulation and decision making?*

Previous research was predominantly concerned with emotions triggered by events that occur within the auction process, i.e. integral emotions (Rick and Loewenstein, 2008). However, many electronic auction platforms employ social images on their websites which are completely unrelated to the present auction task. Recent research examined that social images may manipulate experienced social presence, thereby affecting perception, emotions and even decision making (Hassanein and Head, 2007; Cyr et al., 2009; Steffen et al., 2009). Moreover, research from social psychology found that subjects continuously aim to alter their emotional experience, i.e. use individual emotion regulation strategies in order to deal with emotional stimuli (Gross and John, 2003). Therefore, it is necessary to examine the influence of social images on emotions and decision making, by controlling for the moderating role of subjects' individual emotion regulation strategies, which also can be assessed by psychophysiological correlates.

Finally, a Design Science approach will be pursued, in order to develop a tool that provides its users with information about their emotional state (by employing the heart rate as a proxy) but also rewards emotion regulation skills. This challenge will be tackeled by the following design objective.

> **Design Objective:** *Development of a NeuroIS tool which increases subjects' awareness for their emotional state and rewards emotion regulation capabilities.*

Additionally to a broad body of psychological research on emotion regulation, economic experiments and field studies with practicioners found evidence for a correlation of good emotion regulation skills and beneficial economic and financial decision making (Sokol-Hessner et al., 2008; Fenton-O'Creevy et al., 2011). Since the inability to down-regulate high levels of arousal (i.e. poor emotion regulation) manifests in psychophysiological correlates such as increased heart rate, we attempt to design a NeuroIS tool that, firstly, elicits high levels of physiological arousal in a financial decision scenario and, secondly, rewards the down-regulation of such arousal. In order to satisfy the ensuing design requirements it is necessary to build on advances in the fields of affective computing and neuroergonomics with one of its core concept biofeedback (Nacke et al., 2011).

1.4. Structure of the Thesis

This thesis follows the previously mentioned research questions and is structured in four main chapters, which all detail emotions or emotion regulation and their coherence with decision making in electronic markets. All chapters are based on experimental studies conducted at the Karlsruhe Institute of Technology (KIT). Each study employs psychophysiological indicators in order to assess emotional correlates which can, however, differ depending on the focus of the respective research questions. The results in Chapter 2 and 3 are based on the same experiment. However since they investigate independent research questions, they are introduced separately and can be read independently. Chapter 2, 3 and 4 especially investigate the impact of emotions and emotion regulation on users' decisions in electronic markets. Chapter 5 extends the application set, since the designed and evaluated tool in that chapter is used as built-in function that continuously "adjust(s) to the affective state of the user" (Vom Brocke et al., 2013). Each chapter is structured similarly. The reader is provided with a short introduction, the theoretical background necessary for the topic presented, followed by a description of the design and method. Next the results are presented, followed by a discussion and the conclusion.

In Chapter 2 *we*[4] describe an experiment on regret. The emotional reactions elicited by the loser and winner regret feedback information are compared with each other and their influence on economic decision making is analyzed. Chapter 2 is based on joint research with Marc T.P. Adam, Christine Caroline Jähnig and Stefan Seifert (cf. Astor et al., 2011). Chapter 3 analyzes and compares the psychophysiological patterns resulting from the "joy of winning" and "frustration of losing" in first-price sealed-bid auctions. The remainder of the chapter discusses the results and balances their implications. It is based on joint research with Marc T.P. Adam, Christine Caroline Jähnig and Stefan Seifert (cf. Astor et al., 2013). Chapter 4 investigates how incidental and even subliminal emotions affect physiology and economic decision making, and then analyzes the moderating effects subjects' emotion regulation strategies have on the bidding process and the mediating effect of subjects' affective responses. It is based on joint research with Marc T.P. Adam and Jan Krämer (cf. Astor et al., 2013). Chapter 5 describes the design, implementation and evaluation of a NeuroIS tool for improving emotion regulation. Thereby, three design requirements are defined which must be met along the game evaluation process of the tool. This chapter is based on joint research with Marc T.P. Adam, Petar Jerčić, Kristina Schaaff and Christof Weinhardt (cf. Astor et al., 2013) and on joint research with Petar Jerčić, Marc T. P. Adam, Olle Hilborn, Kristina Schaaff, Craig Lindley, Charlotte Sennersten, Jeanette Eriksson) (cf. Jerčić et al., 2012). Finally Chapter 6 summarizes the key contributions of the thesis, discusses limitations of both the employed methodology and findings, and outlines highly interesting topics for future work.

[4] The *we* refers to both; the readers of this work and my co-authors. I particularly thank Christof Weinhardt, Marc T.P. Adam, Stefan Seifert, Jan Krämer, Christine Caroline Jähnig, Petar Jerčić and Kristina Schaaff.

Chapter 2.

Measuring Regret: Emotional Aspects of Auction Design

Recent research strengthens the conjecture that human decision making stems from a complex interaction of rational judgment and emotional processes. A prominent example of the impact of emotions in economic decision making is the effect of regret-related information feedback on bidding behavior in first-price sealed-bid (FPSB) auctions. Revealing the information "missed opportunity to win" upon losing an auction, results in higher bids. Revealing the information "money left on the table" upon winning an auction, results in lower bids. The common explanation for this pattern is winner and loser regret. However, this explanation is still hypothetical and little is known about the actual emotional processes that underlie this phenomenon. This chapter investigates actual emotional processes in auctions with varying feedback information. Thereby, we provide an approach that combines an auction experiment with psychophysiological measures which indicate emotional involvement. Our economic results are in line with those of previous studies. Moreover, we can show that loser regret results in a stronger emotional response than winner regret. Remarkably, loser regret is strong for high values of "missed opportunity." However, the pattern for different amounts of "money left on the table" is diametric to what winner regret theory suggests.

2.1. Introduction

Meanwhile auctions are "one of the greatest success stories of web-based services" (Ariely and Simonson, 2003, quot. by Adam, 2010). However, our understanding of how rational and emotional processes of human decision making interact in the context of electronic markets is rather limited. Over the last years theoretical research has provided sophisticated economic models which investigate rational bidding behavior (e.g. Krishna, 2002). However, these models do not consider emotional aspects of human decision making. Moreover, experimental tests have shown that the models often fail to accurately predict human decisions. Besides their mathematical beauty, normative models alone are thus not sufficient to fully capture human decision making.

Engelbrecht-Wiggans (1989) states that a bidder's behavior in a FPSB auction does not only depend on the *monetary* profit she expects to gain, but also on two specific *emotions*, namely loser and winner regret. In a FPSB auction, each bidder submits a single sealed-bid. The bidder who has placed the highest bid obtains the item and has to pay the amount of her bid. The bidder suffers from loser regret if she loses the auction, but learns that the object was sold for a price below her own valuation. This means that with a higher bid she could have won the item and made a profit. Contrariwise, a bidder suffers from winner regret if she wins a FPSB auction but gets notice of the second highest bid. She then knows that she has paid more than necessary because with any bid just slightly above the second highest bid she would have won the item at a lower price. The prerequisite for experiencing winner or loser regret is the *feedback* or the information provided in a FPSB auction. In order to experience loser regret (winner regret), the highest bid (second-highest bid) must be revealed to the bidders. Engelbrecht-Wiggans and Katok (2008) confirm this theory by analyzing in a laboratory experiment. However, so far little is known about the actual emotional processes which are responsible for the observed change in behavior. In this chapter, we seek to shed more light on the question to what extent different feedback provided after an auction impacts the emotions and the decisions of human bidders. More specifically, we conduct a laboratory experiment in which we vary the feedback provided to auction participants and measure their physiological correlates of emotional processing. In line with Engelbrecht-Wiggans (1989) and Engelbrecht-Wiggans and Katok (2008), we find a systematic relation between feedback information and bidding behavior. In addition, our results provide psychophysiological evidence for the emotional processing of feedback information in electronic auctions. In terms of psychophysiology, loser regret results in higher physiological responses than winner regret. Thereby, we confirm the theoretical assumption of (Engelbrecht-Wiggans and Katok, 2008) that the intensity of loser regret increases with the amount of missed profit. In contrast to the theoretical assumptions of Engelbrecht-Wiggans and Katok (2008) however, winning an auction at an unfavorable price does not significantly arouse bidders. Rather, winning the auction with exactly the right bid or only one unit too much results in a very strong emotional response. This finding can be explained by considering relief and rejoice as two intense and influential emotions in the bidding process. The remainder of this chapter is structured as follows. In Section 2[1] we provide an overview of how feedback in Information Systems can induce emotions of winner and loser regret. Section 3 presents the experimental design of our study. In Section 4, we present and discuss the economic as well as the psychophysiological results of the experiment. Section 5 concludes.

2.2. Theoretical Background

2.2.1. Regret in Economic Decision Making

Famously Roth (2002) put it in the following quote that *markets don't always grow like weeds—some of them are hothouse orchids.* Thereby Roth targets the multitude of design parameters and mechanisms inherent in market platforms, and their influence on the final market outcome. This applies analogously to *electronic* markets (Weinhardt et al., 2003), where research has for instance also shown that different electronic auction mechanisms can influence the auction outcome to an enormous extent (Lucking-Reiley, 1999). Single variations on auction parameters and mechanism can have material impact on participants' bidding decisions, thereby affecting the auction outcome and seller revenue (Cox et al., 1985). While former theoretical and experimental research specifically compared varying auction mechanisms and the resulting auction outcome in reference to the predicted Nash Equilibrium (Milgrom and Weber, 1982), more recent research has picked up to notion that the understanding of human decision making is a necessary prerequisite for a successful prediction of the auction outcome—and hence for successful auction or market design. Therefore it is essential to understand the agents' behavior and also their emotional processes. Regret appears as one emotion that is suspected to significantly influence subjects' decision behavior in the context of auctions (Engelbrecht-Wiggans, 1989).

[1] Section 2.2 is in close accordance with the work of Adam (2010) on regret, who provides an excellent account on the coherence of this emotion and (auction) decision making.

According to Zeelenberg (1999) “regret is a negative, cognitively based emotion that we experience when realizing or imagining that our present situation would have been better, had we decided differently.” From an economists’ perspective regret was first taken into account by Bell (1982) and Loomes and Sugden (1982), who enhanced expected utility theory by the incorporation of regret. In their model a subject’s utility also depends on the regret someone can experience after the decision is taken. While this experience is *ex post*, anticipated regret can already be taken into account when one is evaluating the options at hand. Thereby, the decision maker tries to avoid the experience of this emotion and changes her behavior towards a regret-minimizing choice (Zeelenberg et al., 1996). The authors state that regret is essential for decision making, which they show in a set of simple gambling experiments. Strikingly, Zeelenberg et al. (1996) finds that subjects’ behavior is in accordance with their regret theory, regardless of whether the decision scenario promotes risk-aversive, or risk-seeking choices. This is highly interesting as, especially in the context of first-price sealed-bid (FPSB) auctions, risk-aversion is regularly employed as an underlying explanation for subjects’ bidding behavior above the risk neutral Nash Equilibrium (Cox et al., 1988). With respect to psychophysiology, Coricelli et al. (2007) state that regret seems also from a neuroscience perspective to be central in human decision making.

2.2.2. Winner and Loser Regret in Auctions

Following the introduction of regret into the field of economics by Bell (1982) and Loomes and Sugden (1982), Engelbrecht-Wiggans (1989) introduced a model which accounts for the emotion regret in FPSB auctions. It is argued that subjects’ utility does not simply depend on the monetary profit, but also on the regret that can be experienced depending on the taken decision. Engelbrecht-Wiggans (1989) particularly refers to winner regret and loser regret in the context of a FPSB auction. Winner regret can be experienced after the bidder has won the auction upon being informed about the second highest bid. The difference between the winning and the second highest bid is referred to as the “money left on the table.” This is the amount of money which the winner of the auction could have gained more by placing an even lower bid. To the contrary, loser regret can be experienced only after losing an auction. After losing, the revelation of the winning bid informs the bidder about the “missed opportunity”, i.e. about the amount of money which the bidder could have won in the auction by placing a higher (optimal) bid. It is important to note that the experience of winner or loser regret may influence subjects' subsequent bids. However, even the information, that subsequently to the FPSB auction the information of the highest or second highest bid will be revealed, could potentially increase subjects' anticipation of winner and loser regret, and thereby shift their bidding strategies. In his developed model Engelbrecht-Wiggans (1989) shows analytically, under the assumption of identical weights of winner and loser regret, that a subject's bidding strategy is invariant of the incorporation of regret. However, if, as one might assume, loser regret exceeds winner regret, than this should be reflected in on average higher bids compared to the risk neutral Nash Equilibrium (RNNE). It has long been known that bidders in FPSB auctions place considerably higher bids, than the symmetric RNNE bidding strategy by Vickrey (1961) would predict (Kagel, 1995). Before emotions were taken into account, but also up to today, bids exceeding the RNNE are typically explained by the RNNE. However, as shown above, also the anticipation or experience of loser regret could be a major influencing factor for individuals decision behavior. In this context, Kagel (1995) argues that "risk aversion is one element, but far from the only element, generating bidding above the RNNE"(quot. by Adam, 2010).

Several studies have meanwhile examined the influence of winner and loser regret on decision making in the context of FPSB auctions. Specifically two studies in recent years have drawn much attention. In a laboratory experiment with between-subject design Filiz-Ozbay and Ozbay (2007) specifically investigate the influence of anticipated regret on subjects decision making in a one-shot FPSB auction. Depending on the assigned treatment, subjects solely receive subsequently to the auction the information on the second highest bid (winner regret), on the highest bid (loser regret), or no such information. Filiz-Ozbay and Ozbay (2007) employ a one-shot design, in order to assure that learning effects can be excluded and that anticipated regret has to be the driver for subjects decision behavior. The authors find support for loser regret, but not for winner regret, as they compare the two treatment groups against the control group which does not receive any feedback information. Additionally, by the usage of post-auction questionnaires, Filiz-Ozbay and Ozbay (2007) state that loser regret is experienced stronger than winner regret, whereas winner regret is still experienced to some extent. Contrary, to the one-shot experiment by Filiz-Ozbay and Ozbay (2007), Engelbrecht-Wiggans and Katok (2008) follow the intuition that regret needs to be experienced a couple of times in the context of auctions, before one starts to anticipate it and before one incorporates it into his or her decision process. Engelbrecht-Wiggans and Katok (2008) employ a between-subject design with similar treatment groups as Filiz-Ozbay and Ozbay (2007).[2] Moreover, they control for learning effects, as participants participate in a series of FPSB auctions. Independently of the observation that bids decrease in the four treatment conditions over time, Engelbrecht-Wiggans and Katok (2008) find significant support for both winner and loser regret. However, it must also be mentioned that recently there have been negating findings with respect to the influence of regret in auctions. Katušcák et al. (2013) find no systematic influence of loser regret in their experimental data set. The authors come up with two essential observations. First, subjects assigned to the loser regret condition do not place higher bids than the control condition; Second, also subjects in the control condition employ “overbidding” to a large extent.

The main focus of this chapter is to investigate the impact of different information feedback elements on the emotional processing and bidding behavior of human individuals in electronic markets. In short we focus on the following research questions: (1) Can the emotional processes of regret be manipulated by systematically varying information feedback and (2) how are these emotions reflected in bidding behavior? Therefore, we conduct a laboratory experiment, in which we manipulate the feedback information in FPSB auctions.

2.3. Design and Method

The experiment is similar to the experiment conducted by Engelbrecht-Wiggans and Katok (2008). However, while Engelbrecht-Wiggans and Katok (2008) cannot determine to what extent the information feedback induces the emotion regret, we use psychophysiological measurements in order to directly determine the intensity of emotions in the moment they actually occur. More specifically, we continuously measure the participants’ skin conductivity as a proxy for their emotional processing (cf. Dawson et al., 2007). Skin conductivity is a reliable indicator for arousal as it reflects the intensity of an ongoing emotional process. In compliance with the theory of induced values (Smith, 1976), all decisions in this experiment are directly related to real monetary payoffs. This means that each bidder has to accumulate so-called *monetary units (MU)*, which are in-

[2] Additionally, Engelbrecht-Wiggans and Katok (2008) design a fourth treatment condition, which receives both feedback information, loser regret and winner regret.

dividually converted into Euro and paid out in cash after the experiment. Thereby, 1 MU is equivalent to €0.03. Initially subjects are endowed with 100 MU as a lump sum payment. Monetary units were chosen to keep the payment scheme simple and that feasible bids were integers. This procedure is state-of-the-art in economic experiments (Guala, 2005). With respect to reliability of economic experiments Falk and Heckman (2009) note that "behavior in the laboratory is reliable and real: Participants in the lab are human beings who perceive their behavior as relevant, experience real emotions, and take decisions with real economic consequences" (quot. by Adam, 2010).

2.3.1. Treatment Structure

Table 2.1.: Experimental Design

	Treatment Conditions		
	Loser Regret (LR)	**No Regret (NR)**	**Winner Regret (WR)**
Display of *missed opportunity* (MO)	yes	no	no
Display of *money left on the table* (MLOTT)	no	no	yes
Number of subjects per treatment	24	30	24
Number of sessions	4	5	4

As depicted in Table B.1, the experiment comprises three treatments: *Loser Regret (LR)*, *Winner Regret (WR)*, and *No Regret (NR)*. The experiment is based on a between-subject design (Kagel, 1995), i.e. subjects exclusively participate in the LR, WR, or NR treatment. The treatments vary in the form of feedback information provided to the bidders after an auction ends. In the LR treatment, bidders are provided with information regarding the highest bid in case of losing an auction. The amount of "missed opportunity" is provided, i.e. the maximum profit a bidder could have gained ex post by placing a higher bid. This amount equals to the own valuation v_i minus the highest bid. Thereby, a bidder can learn ex post that she actually could have gained a profit by placing a higher bid. In the WR treatment, bidders are provided with information regarding the second-highest bid in case of winning an auction. The amount of "money left on the table" is provided, i.e. the difference between the winning bid and the second highest bid. Thereby, a bidder can learn ex post that she actually paid too much and could have gained a higher profit by placing a lower bid. In contrast, in the NR treatment, bidders are only informed whether they won or lost an auction. They do not obtain any information regarding bids of the other bidders. The experimental system is implemented using z-Tree (Fischbacher, 2007). In order to allow for analyzing physiological reactions in response to single information events, the feedback information is provided in timed intervals. After the end of an auction, first a bidder is only informed whether she won or lost the auction. After 5 seconds, the “missed opportunity” and “money left on the table” information is displayed in the LR and WR treatments, respectively. In the NR treatment, no additional information is provided. Figure 2.1 illustrates the auction process.

2.3.2. Auction Process

In the experiment, each bidder takes part in a series of 50 FPSB auctions. Similar to Engelbrecht-Wiggans and Katok (2008), each subject bids against two computerized agents to exclude social preferences and other interpersonal effects. Thus, there is no strategic interaction with other human bidders in this experiment. In each auction, the human and the computerized bidders each receive an individual valuation v_i for the item for sale in the auction. Then, each bidder i individually has to decide for an integer bid b_i between 0 MU and 100 MU. The bidder who placed the highest bid wins the auction and has to pay the amount of her bid. The incentive for participating is to obtain the profit $\Pi_i = v_i - b_i$ in the case of winning. In the case of a draw, the human bidder automatically wins. The computerized agents independently draw valuations form a uniform distribution with support on the integer set $\{0, 1, 2, \ldots, 100\}$ MU. Following the symmetric Nash equilibrium of Vickrey (1961), each computerized agent places a bid b_i according to the function $b_i(v_i) = (2/3)v_i$, rounded to the nearest integer, in all treatments. Thereby, the computerized agents assume that the valuations of the human bidder stem from the same distribution as their own valuations. However, following the approach of Engelbrecht-Wiggans and Katok (2008), the human bidder receives her valuation from a permutation of the values 50 MU, 60 MU, 70 MU, 80 MU, and 90 MU. The bidder keeps a randomly chosen valuation for 10 consecutive auctions. For instance, a bidder receives the valuation of 80 in the first auction and then keeps this valuation until she receives a new valuation in the eleventh auction. Section 3.3.2 provides a more detailed description of the bidding mechanism.

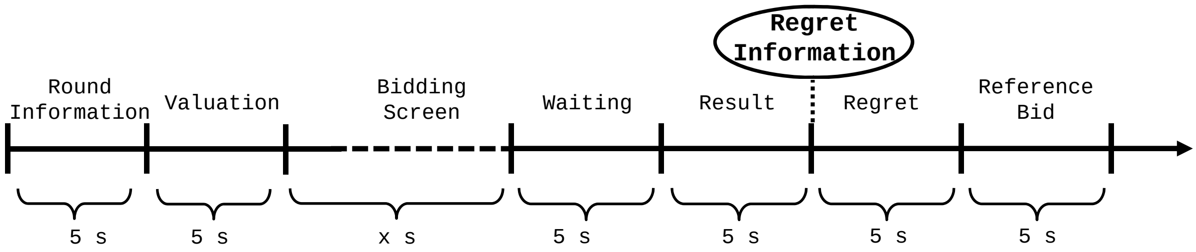


Figure 2.1.: Illustration of the Auction Process with the Regret Information being Displayed at 'Regret Information'

2.3.3. Procedure

This laboratory experiment was conducted at the KIT, Karlsruhe, Germany. Participants were recruited from a pool of undergraduate students using the ORSEE software environment (Greiner, 2004). Altogether 78 (19 female and 59 male) subjects participated in 13 sessions. Each session lasted approximately 1.5 hours. In this experiment, the average payment was €19.82, with €12.30 and €23.01 being the minimum and maximum payments, respectively. During the whole experiment, participants' skin conductance was measured with a constant current amplifier measurement system and Ag/AgCl (silver/silver chloride) electrodes. The electrodes were attached on the thenar and hypothenar eminences of the palm of the non-dominant hand by use of standard EDA electrode paste (cf. Boucsein, 1992)). See Adam (2010) for a more detailed description. Following the recommendations of Schmidt and Walach (2000) an initial five minute rest period is conducted during this preparation phase for calibration purposes. Moreover, participant interactions with the experimental system is limited to mouse inputs and participants are equipped with a pair of ear-muffs to avoid sensitivity to background noise. All sessions were conducted in spring 2010 with an average room temperature of 25 °C (77 °F). These values are within the methodological recommendations of the Society for Psychophysiological Research (cf. Fowles et al., 1981). One subject had to be removed from the whole dataset due to failed comprehension. For one session in the NR treatment, physiological measurements failed to operate. Moreover, 12 participants turned out to be non-responders regarding electrodermal activity, i.e. they do not show physiological responses. Hence, the economic analysis is based on 77 participants. The physiological analysis is based on 59 participants.

2.3.4. Measures

We accounted for the *bids* in the respective treatment conditions. The emotional response is assessed by analyzing the skin conductivity data. The skin conductance response amplitude (SCR.amp) is a proxy for the intensity of immediate emotions induced by a discrete stimulus. Since this response usually occurs 1 to 3 seconds after the respective event (Boucsein, 1992; Schmidt and Walach, 2000), only those amplitudes that were observed within that time frame were taken into account. Furthermore and in line with Fowles et al. (1981), only amplitudes greater or equal to .01 μS were considered. The SCR amplitudes were obtained by decomposing skin conductivity into its tonic and phasic components using the Ledalab analysis software (Benedek and Kaernbach, 2010). Following the recommendation of Venables and Christie (1980), all SCR.amp values x were then transformed according to $log(x+1)$ in order to reduce the inherent left skewness of the SCR.amp. In the analysis, we focus specifically on the average SCR.amp in response to learning different feedback information in the LR and WR treatment, respectively. Additionally, we assessed demographic factors such as age and sex.

2.4. Results

In this section we present and discuss the economic as well as the psychophysiological results of the experiment. The key focus of the analysis is to investigate how the provision of loser and winner regret information changes the emotional processing of participants, and if this emotional process is linked to actual bidding behavior. For more information regarding subjects' general bidding behavior see Section

2.4.1. Feedback Information and Bidding Behavior

First we focus on how different feedback information influences bidding behavior. Following the theoretical predictions of Engelbrecht-Wiggans (1989), providing the bidders with the loser (winner) regret information should result in higher (lower) bids. This is reflected in the Hypotheses H1a and H1b:

> **H1a:** *Bidders place higher bids, if they are informed about missed opportunities (LR treatment) in comparison to the NR treatment.*

> **H1b:** *Bidders place lower bids, if they are provided with the information how much money they "left on the table" (WR treatment) in comparison to the NR treatment.*

Figure 2.2 depicts box plots for the distribution of bids in the three treatments of the experiment. The box plots show the quartiles of the bids, as well as the minimum and maximum observation. As stated in hypothesis H1a, the bids in the LR treatment are above the bids in the NR treatment. Moreover, and in line with hypothesis H1b, the bids in the WR treatment are below the bids in the NR treatment. In order to analyze whether the results are comparable with previous work, we calculate the ratio of a bidder's valuation and her actual bid, the so-called bid/value ratio (b/v).

The average bid/value ratios of our experiment are summarized along with the previous results in the literature in Table 2.2. In parentheses, the standard deviations are given. Our economic results are in line with those of previous studies. Filiz-Ozbay and Ozbay (2007) observe *bid/value* ratios of .79 and .77 for subjects in the NR and LR treatments, respectively.

Table 2.2.: Summary of Bid-Value Ratios

	Treatment Conditions		
	Loser Regret (LR)	**No Regret (NR)**	**Winner Regret (WR)**
Filiz-Ozbay and Ozbay (2007) (4 bidders per auction)	.87	.79	.77
Engelbrecht-Wiggans and Katok (2008) (3 bidders per auction)	.776 (.048)	.715 (.069)	.697 (.065)
Present study (3 bidders per auction)	.756 (.057)	.729 (.061)	.696 (.050)

In contrast, subjects in the LR condition place significantly higher bids (.87). Engelbrecht-Wiggans and Katok (2008) report average bid-value ratios of .77 for LR

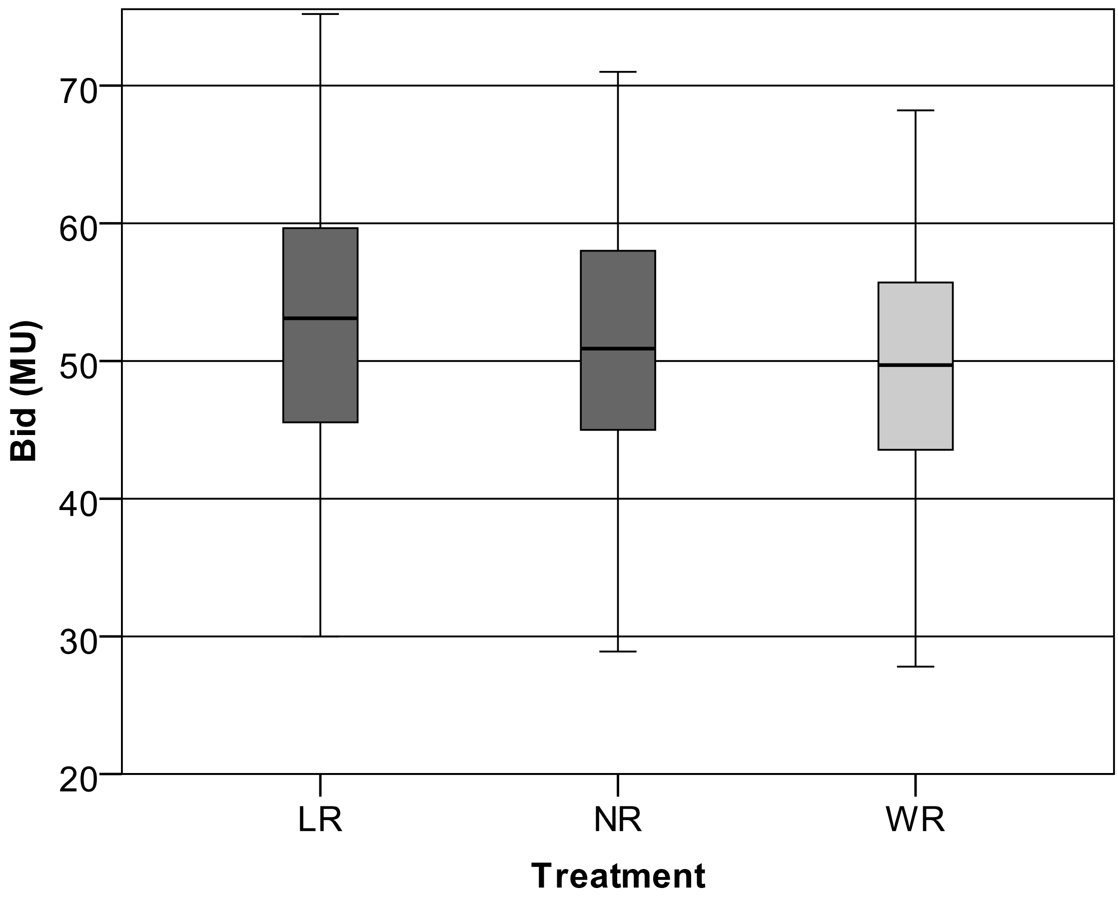


Figure 2.2.: Bids for Each Treatment

bids. Subjects exposed to LR and NR place bids of .72 and .70, respectively. In all three experiments, the bidders on average place their bids above the theoretical benchmark of the Nash equilibrium bidding strategy.

We use an Ordinary Least Square (OLS) regression model, in order to test the statistical significance of loser regret and winner regret on the bidders' bids. Different to Engelbrecht-Wiggans and Katok (2008) we explicitly look at the valuation {50, 60, 70, 80, 90} as independent and the bid as dependent variable rather than only the bid/value ratio as dependent variable. Thus, with 77 subjects in the economic analysis and 5 observations per subject, the regression is based on 385 observations. Table 2.3 shows the results of the OLS regression. In line with hypothesis H1a, bidders place *higher* bids in the LR treatment in comparison to the NR treatment (B = 1.858, se = .651, t = 2.853, p < .01). Therefore, we can reject the null hypothesis that "missed opportunity" feedback information has no impact on bidding behavior in favor for hypothesis

Table 2.3.: Regression Model for Bids

	Dependent Variable Bid				
Independent variables	**B**	**SE**	***t*-Stat**	***p*-value**	**Sig.**
value	.465	.651	24.480	<.001	***
Loser Regret (LR)	1.858	.651	2.853	.005	**
Winner Regret (WR)	-2.292	.767	-3.520	<.001	***
c (constant)	18.888	1.991	9.488	<.001	***
	$n = 77$ x 5 $R^2 = .626$				

* $p < .05$, ** $p < .01$, *** $p < .001$

H1a. Moreover, and in line with hypothesis H1b bidders place *lower* bids in the WR treatment in comparison to the no regret treatment ($B = -2.292$, $se = .767$, $t = -3.520$, $p < .001$). Therefore, we can also reject the null hypothesis that "money left on the table" feedback information has no impact on bidding behavior in favor for hypothesis H1b. In summary, we conclude from the economic data that bidders place higher bids in the LR treatment (hypothesis H1a) and lower bids in the WR treatment (hypothesis H1b). When taking a closer look at the constant term c of the regression, one can observe that c is above zero (18.888). Thus, including a bidder's valuation v in the analysis allows for a more finely grained analysis than the simplified bid/value ratio used for reasons of comparability with the other studies in Table 2.3 which implicitly assume that c is zero.

2.4.2. Feedback Information and Emotional Intensity

The bidders' log transformed average SCR.amp in response to receiving the "missed opportunity" and "money left on the table" feedback information for the LR and WR treatment are depicted in Figures 2.4 and 2.5. As by construction there is no such feedback information provided in the NR treatment, there are also no physiological responses to feedback information in the NR treatment. Little is known about subjects' *actual* emotional processing in response to varying regret feedback information in FPSB auctions. Engelbrecht-Wiggans and Katok (2008) argue that the utility a bidder derives from a FPSB auction does not only depend on the monetary gains and losses, but also on the degree of winner and loser regret. According to Engelbrecht-Wiggans and Katok (2008) the perceived *ex ante* expected utility of a bidder with valuation v and bid b is

$$\Pi(b,v) \equiv (v-b)F(b) - \int_{z:z\leq b} \alpha(b-z)dF(z) - \int_{z:b\leq z\leq v} \beta(v-z)dF(z)$$

where z denotes the highest bid made by the competitors (Engelbrecht-Wiggans and Katok, 2008). F denotes the cumulative distribution function of z. The first part of the formula refers to the expected monetary payoff as postulated by standard auction theory. The latter part takes into account the disutility of winner regret and loser regret, respectively. The amount of "missed opportunity" translates into $(v-z)$. The amount of "money left on the table" translates into $(b-z)$. The coefficients α and β refer to the weight of winner and loser regret, respectively. Engelbrecht-Wiggans and Katok (2008) theoretically show that if bidders equally weigh winner and loser regret ($\alpha = \beta$), then regret has no influence on decision making in FPSB auctions. However, the authors conclude from their experimental results that "participants put more weight on the loser's regret than on the winner's regret" ($\alpha < \beta$). We specifically analyze the bidders' emotional response in the very moment the bidders learn about their "missed opportunity" and "money left on the table," respectively. Thereby, we test the conjecture that the loser regret is weighted stronger than winner regret ($\alpha < \beta$). This translates into hypothesis H1c.

> **H1c:** *The emotional response to the feedback information in the LR treatment ("missed opportunity") is stronger than in the WR treatment ("money left on the table").*

As depicted in Figure 2.3, and in line with H1c, the physiological response to the feedback information in the LR treatment is stronger than the response to the feedback information in the WR treatment. Therefore, we reject the null hypothesis in favor of H1c (.104 vs. .076, $n = 185$, $t(183) = 2.092$, $p < .05$). The bidders in fact show a stronger emotional response to the feedback information in the LR treatment. This is in line with the assumption of Engelbrecht-Wiggans and Katok (2008) that the participants weigh the loser regret information stronger than the winner regret information ($\alpha < \beta$). After observing the differences between the WR and LR treatment, we will now turn our focus on subjects' varying physiological responses within the two regret treatment groups.

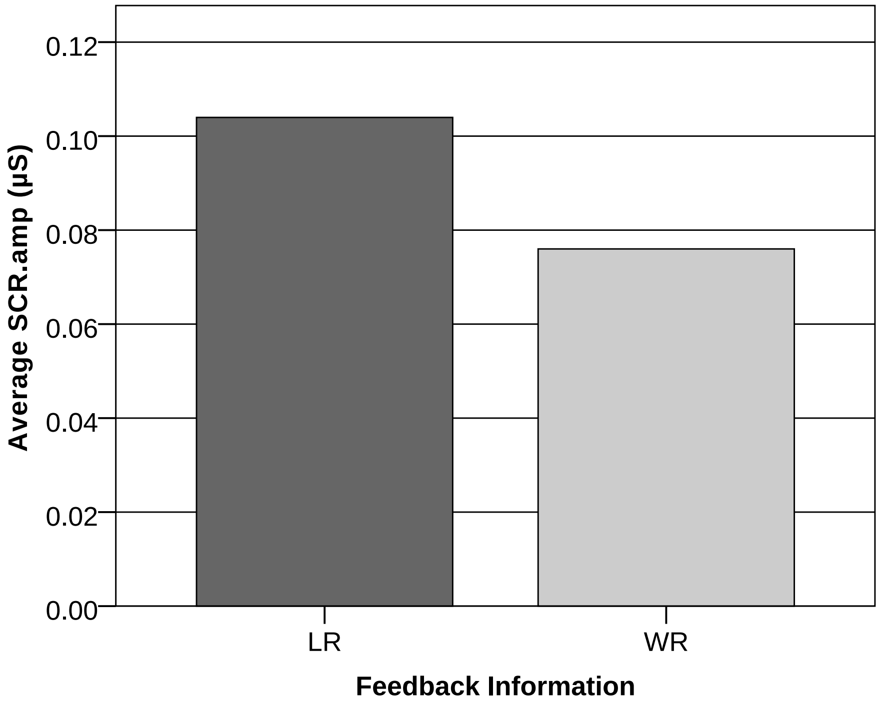


Figure 2.3.: Average SCR.amp to Loser Regret Information and Winner Regret Information

2.4.3. Emotional Intensity of the Loser Regret Information

First we take a closer look on the emotional processing of the LR feedback information. Engelbrecht-Wiggans and Katok (2008) state that "regret enters additively into the bidder's utility function, and that the effect of regret on the bidder's utility function is proportional to the amount of regret suffered." Following this statement, we would assume that the experienced regret increases with the value of the "missed opportunity." In the utility function of Engelbrecht-Wiggans and Katok (2008) as depicted in Section 2.4.2, this translates into the term $\beta(v-z)$ If this is true, the bidders' emotional response should be stronger for increasing values of $(v - z)$ This translates into hypothesis H1d:

> **H1d:** *The emotional response to the feedback information in the LR treatment is stronger for high amounts of "missed opportunity" than for low amounts of "missed opportunity."*

The bidders' log transformed average SCR.amp in response to learning the regret information in the LR treatment for different amounts of "missed opportunity" is depicted in Figure 2.4. Each class consists of similar sample sizes. Figure 2.4 indicates

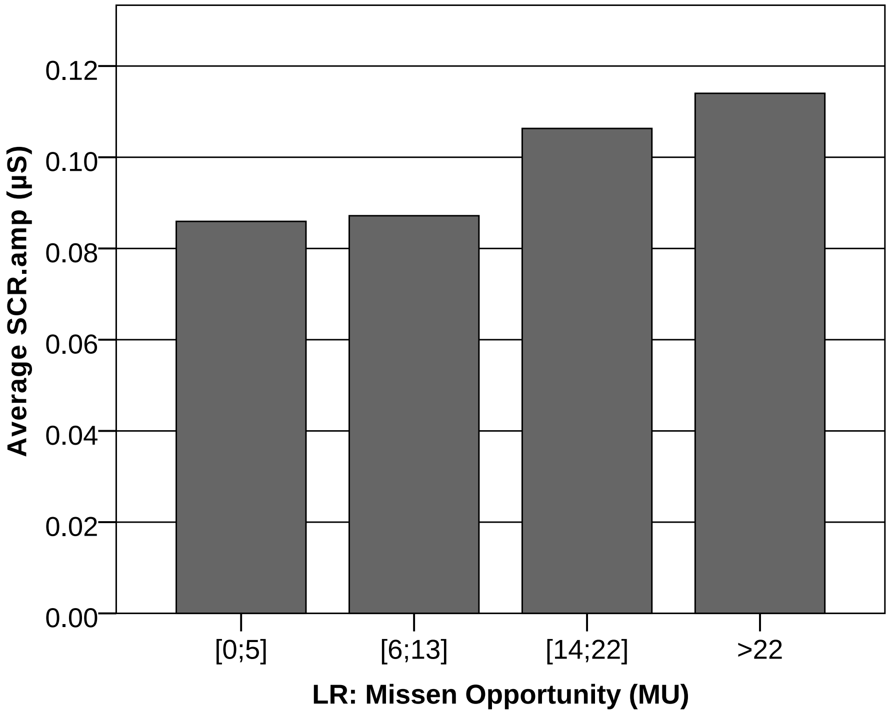


Figure 2.4.: Average SCR.amp to Different Classes of Loser Regret Information

that the psychophysiological response increases with higher amounts of "missed opportunity." This is in line with our hypothesis H1d. The correlation between the emotional response and the increasing degrees of "missed opportunity" is not significant for these 4 classes. Therefore, we cannot reject the null hypothesis. We attribute this to the high between-subject variability of skin conductivity and the low number of observations for different degrees of "missed opportunity." However, when merging observations into two classes with similar sample sizes, a one-sided t-test reveals that the emotional response to the two different classes of MO is marginally significantly different (.087 vs. .110, $n = 174$, $t(172) = -1.363$, $p < .10$).[3] At this stage, we can conclude that "missed opportunity" leads an intense emotional response, which is stronger than the "money left on the table" information. The question whether higher amounts "missed opportunity" result in stronger emotional responses will have to be investigated in future research.

[3]Note, that this analysis is slightly modified compared to Astor et al. (2011) as four physiological non-responders were excluded; however, the main results are invariably robust against this procedure.

2.4.4. Emotional Intensity of the Winner Regret Information

In the next step the emotional processing of the WR feedback information will be analyzed. According to Engelbrecht-Wiggans and Katok (2008) the winner regret should also rise with increasing amounts of "money left on the table." In the utility function as depicted in Section 2.4.2, this is reflected in the term $\beta(b-z)$. When regret increases with the amount of money left on the table this also should be observable within the physiological data. This translates into hypothesis H1e:

> **H1e:** *The emotional response to the feedback information in the WR treatment is stronger for high amounts of "money left on the table" than for low amounts of "money left on the table."*

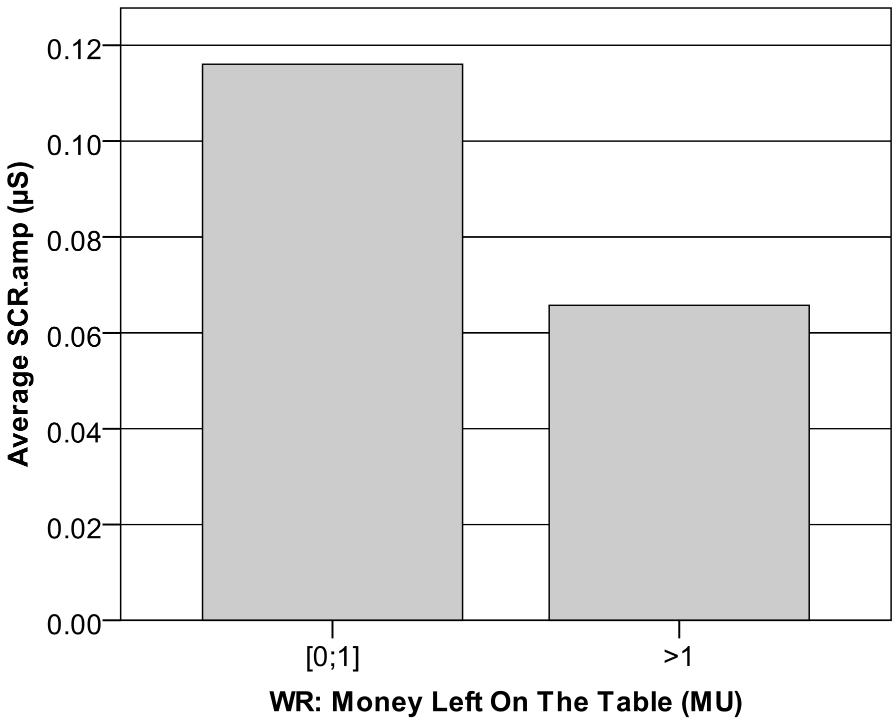


Figure 2.5.: Average SCR.amp to Different Classes of Winner Regret Information

In contrast to the last section, the physiological data does not support the model of Engelbrecht-Wiggans and Katok (2008) regarding the winner regret. Quite to the contrary, the bidders experience high intensities of emotional processing for low values of $(b-z)$. The bidders' log transformed average SCR.amp in response to learning the regret information in the WR treatment for different amounts of "money left on the table" is depicted in Figure 2.5. Very small values of "money left on the table" (i.e. values of 0 or 1) induce very high physiological responses. On the other hand, high amounts of "money left on the table" result in relatively small responses (.116 vs. .066, $n = 395$, $t(393) = 2.484$, $p < .05$). Taking into account the physiological data, it seems that actually the experience of winning an auction with a very small amount ahead reveals relief or a thrill of winning and is central to participants. Suffering from winner regret on the other hand, when winning at a not optimal price, does not seem to be central in subjects' emotional experience. Therefore, we state that winner regret is only minor and not that important in subjects' emotional processing compared to loser regret. This high response can be interpreted as relief or even thrill of winning instead of winner regret, since the bidder won by a very small amount.

2.5. Discussion and Conclusions

2.5.1. Theoretical Implications

The hypotheses in the present study are closely linked to those of Engelbrecht-Wiggans and Katok (2008). The majority of the initial hypotheses are supported by our data. This confirms the view that emotions, more specifically regret, can be deliberately elicited by well planned design features of Information Systems. In addition our data strengthens the claim that these design features can also influence bidding decisions. Our results do not only support the original view of how regret effects bidding behavior. The original hypothesis that the intensity of winner regret increases with the amount of "money left on the table" is challenged by the present study. With the support of physiological measures it becomes apparent that bidders show a stronger reaction to near gains, than to huge amounts of "money left on the table." Different explanations for this deviation from theory are possible. It is possible that feelings of relief and rejoice outweigh the importance of winner regret. Engelbrecht-Wiggans and Katok (2008) point to a similar explanation. Regarding their experiment Engelbrecht-Wiggans and Katok (2008) state "that subjects tend to anticipate loser's regret, but tend not to anticipate winner's regret until they have experienced it a couple of times." Since *loser regret* is more intuitive than *winner regret*, this could be an explanation for the differing emotional responses. Alternatively, *loser regret* after losing an auction could simply be more arousing than *winner regret* after the experience of winning. The good experience of winning cannot be distracted by the information of how much “money (was) left on the table.”

2.5.2. Limitations

With respect to the economic analysis the valuation, which subjects received, picks up lots of explanatory power in this experiment, each subject entered the regression with five observation points—one for each valuation. Reducing the statistical analysis to one observation per subject leads to weaker results due to the limited number of participants. With respect to psychophysiology, 20 subjects were analyzed for each treatment condition. Similarly to the economic analysis the comparison of loser versus winner regret was based on five responses per subject—one for each valuation of each subject. With respect to the more detailed analyses on winner and loser regret, observations were taken independently into account. Due to this procedure, the exploratory power of tests and regressions employed in this experiment might be limited. Therefore, the explanatory power of our findings have to be taken with a grain of salt.

2.5.3. Conclusions

Including emotions into economic models of human behavior in electronic markets has been long overdue. Engelbrecht-Wiggans and Katok (2008) developed such a model for bidding in FPSB auctions that includes two very decision relevant emotions, namely loser regret and winner regret. Although the model has been tested empirically the integration of emotions into the bidding process is based on purely theoretical assumptions. The present chapter fills this gap by actually measuring bidders’ physiological reactions to regret relevant information. Resulting from the cited previous work on regret in FPSB auctions two major research questions were posed: (1) Can the emotional processes of regret be manipulated by systematically varying information feedback and (2) how are these emotions reflected in bidding behavior? The first questions can be answered with a clear “yes.” As depicted in Figure 2.3 bidders experience more intense emotions, upon receiving loser regret information compared to receiving winner regret information. The second research question can only be answered in parts. Even though different feedback information elicits different physiological patterns and significantly different bidding behavior, the relationship between bidding behavior and emotional response is a complex interaction of cognitive and emotional processes, including regret and relief. In order to better understand this relationship, there is a need for future research. In the present chapter we have only reported on skin conductance as an indicator for the intensity of emotions. In the next chapter also the question how winning and losing itself is experienced in a FPSB auction. Thereby, the physiological parameter heart rate will be employed as it is especially of use to gain more insight about the valence associated with the auction outcome.

Chapter 3.

The Joy of Winning and the Frustration of Losing

As examined in the last section subjects experience regret in response to a feedback information indicated ex post after they already know about the auction outcome. There is also literature which suggests that the auction outcome itself elicits an aversive “frustration of losing,” as well as a rewarding “joy of winning” response. However, little is known about the intensity of these emotional reactions and how they relate to other factors in the auction process. In this chapter, we continue our investigation of how subjects experience winning and losing in the FPSB auction. The psychophysiological measures SCR and heart rate (HR) were recorded as proxies for both the intensity and the valence of emotions. Our results show that the deceleratory responses in HR when losing an auction are stronger than when winning an auction. The drop in HR itself can be interpreted as a reaction to stimuli with negative emotional valence. Moreover, we find that winning an auction induces a stronger SCR compared to losing an auction. An explanation for this pattern is that subjects try to inhibit or regulate their negative emotions after losing an auction—the concept of Emotion Regulation will be examined more deeply in Chapter 4. Interestingly, this distinction in emotional response between winning and losing even holds for different value classes and different amounts of payoffs. Moreover, we can show that bidders’ SCR.amps increase in the relation to the amount of money at stake. However, it is not possible to definitely determine as to whether the valuation triggers this effect or the potential nominal payoff.

3.1. Introduction

Auctions, especially online auctions, have become increasingly popular in the last decade (Ariely and Simonson, 2003). What makes auctions so attractive despite the fact that they sometimes result in even higher prices than fixed price offers on retail sites (Lucking-Reiley, 1999; Malmendier and Szeidl, 2008)? According to Bapna et al. (2001), the purchase decision of consumers is based on whether they want to buy something at an unexciting fixed price (e.g., amazon.com) or experience the “bazaar-like competitive atmosphere” of an online auction (quot. by Adam, 2010). Stafford and Stern (2002) argued that the emotions bidders experience in online auctions are a source of hedonic shopping value, and thus a distinctive feature of online auctions in comparison to fixed price retail sites. Lee et al. (2009, p.93) claimed that the “thrill of bidding, excitement of winning, [and the] stimulation of beating competitors” play an important role in why consumers choose to participate in online auctions (quot. by Adam, 2010). In this regard, they supported Herschlag and Zwick (2000) conjecture that “winning is the aphrodisiac that gets the shopping juices flowing” and that the joy of winning is the main driver of the special shopping experience of online auctions. In this chapter, we analyze the emotions or, more concisely, the immediate emotions that bidders experience when winning or losing an auction. In the literature, these emotions are commonly referred to as the “joy of winning” (Andreoni et al., 2007) and the “frustration of losing” (Ding et al., 2005). However, only little is known about how bidders actually experience these emotions and what their determinants are. Therefore, we argue that a deeper understanding of the bidders’ emotions may facilitate building more sophisticated economic models that include the valence and intensity of emotions in the bidders’ utility functions. In particular, this study looks at whether winning or losing an auction has a greater impact on bidders in terms of emotional intensity and how the different emotional values of winning and losing are reflected in the distinct patterns of HR changes. In order to do this, we conducted a laboratory experiment, in which subjects participated in a series of FPSB auctions. Some prominent examples of FPSB auctions include auctions of U.S. treasury bills, Japanese Fish Markets, or closed bids for real estate in the private sector. In an FPSB auction, each bidder submits a single sealed bid. The bidder who places the highest bid obtains the item and has to pay the amount of his or her bid (Vickrey, 1961). In order to monitor the emotional reactions that accompany the bidding process, we actually measure the galvanic skin conductance of the subjects and an electrocardiogram is used to record their response to the auction outcome. These physiological parameters are well-established proxies for emotional processing in psychophysiology (Boucsein, 1992; Berntson et al., 2007).

The results provided in this chapter allow us to draw conclusions about how people experience auctions. Since emotions may significantly impact the behavior of individuals (Zeelenberg, 1999), analyzing emotional reactions in auctions will help to better understand consumer behavior. The applied methodology in terms of galvanic skin conductance response resulted in physiological data which showed a stronger response to winning an FPSB auction than to losing an auction. This indicates that winning an auction is processed more intensely than losing an auction. Moreover, participants experience winning and losing more intensely when the valuation for the good being auctioned is higher. The physiological data also gives some indication regarding the valence of the respective emotions. In fact, losing an auction causes a significant drop in HR. This response is similar to the phasic changes in HR that were observed in previous studies. For instance, Bradley et al. (2008) reported deceleratory responses when participants were shown pleasant and unpleasant pictures. These deceleratory responses were stronger for unpleasant pictures in comparison to pleasant pictures. Thus, we suspect that the observed drop in HR in response to losing a FPSB auction is also a reflection of an unpleasant emotion, which we interpret as a sign of frustration. The remainder of this chapter is structured as follows: We first provide an overview of the emotions that bidders may experience when winning or losing an auction.[1] Based on this theoretical background, we outline the experimental design of our study. Then, we present and discuss the results of the experiment. Finally, the last section concludes and discusses the outlook for future research.

3.2. Theoretical Background

3.2.1. The Joy of Winning and the Frustration of Losing

Emotions play an important role in human decision making (Elster, 1998; Rick and Loewenstein, 2008; Steffen et al., 2009). In this chapter, we define an emotion according

[1] Parts of Section 3.1 and 3.2 are in strong accordance with Adam (2010), who provides a very good account of the emotions afflicted to winning and losing in the context of auctions.

to Myers (2004, p. 500) as a subjectively experienced state that is characterized by conscious experience, which is generally accompanied by expressive behavior and physiological arousal. Emotionally arousing stimuli usually elicit physiological responses (Boucsein, 1992; Bechara et al., 2005). This means that the subjectively experienced emotion is related to objectively observable physiological parameters which can be interpreted as proxies of the actual emotion. Emotional stimuli are often characterized in the two dimensions of valence and arousal (Gläscher and Adolphs, 2003). These two dimensions are reflected in different physiological indices (HR and SCR) and serve to index emotional processing (Lang et al., 1993). We measure these physiological reactions of human bidders while they are participating in a series of FPSB auctions.

In particular, we focus on the physiological reactions exhibited when the auction outcome is revealed (Adam et al., 2011). In single unit auctions, the auction outcome determines which bidder obtains the commodity for sale and how much he or she has to pay for it. Traditional auction theory, which is based on game theory and mathematical models, only considers the monetary utility associated with this auction outcome (Vickrey, 1961; McAfee and McMillan, 1987). However, the bidders may also derive (non-monetary) utility from winning the inherent competition of an auction that is "over and beyond any monetary payoffs" (Cooper and Fang, 2008, Roider and Schmitz, 2012, quot. by Adam, 2010). In our experiment, we emphasize the competitiveness of auctions by referring to the bidder who obtains the item as the "winner" and all other bidders as the "losers" of an auction. This terminology is based on the perceptions of bidders as reported by Ariely and Simonson (2003) who found in an Internet survey that 76.8 per cent of the respondents considered other bidders as "competitors" and referred to auction outcomes as "winning" or "losing" (quot. by Adam, 2010).

In the literature, the emotion triggered by the event of winning an auction and receiving a positive monetary payoff has been referred to as the "joy of winning" (Goeree and Offerman, 2003; Andreoni et al., 2007). According to Ockenfels et al. (2006), this utility stems from the "thrill of competing against other bidders" (quot. by Adam, 2010). Similarly, Fliessbach et al. (2007) argued that in addition to a monetary reward, "outperforming someone else" can also induce the joy of winning (quot. by Adam, 2010). Ertaç et al. (2011) suggested that the "joy of winning" explains the willingness-to-pay to enter an auction of male bidders to a greater extent than it explains the willingness-to-pay of female bidders. Other authors also refer to this non-monetary incentive component as a “love of winning” (Morgan et al., 2003, Kogan and Morgan, 2009, quot. by Adam, 2010). In contrast, if a bidder loses an auction, he or she may experience the “frustration of losing” (Ding et al., 2005). Adam et al. (2012) found that due to the “click-to-win” characteristic of Dutch auctions, the frustration of losing a Dutch auction is experienced stronger than the joy of winning a Dutch auction. According to Cramton et al. (2012), internalized “fear of losing” can lead to higher bids in clock auctions (quot. by Adam, 2010). Following the reasoning of Delgado et al. (2008), this frustration stems from “losing the social competition” (quot. by Adam, 2010). Therefore, it is an inherent characteristic of auctions that the shopping experience results in either a “rewarding” or an “aversive” emotion (Frijda, 1986) at the end of the auction. Table 3.1 provides an overview of selected literature on the joy of winning and the frustration of losing.

While the joy of winning or the frustration of losing are rather intuitive concepts, there is a debate in the literature as to which of these two emotions has a greater impact on bidders and how these emotions influence future bidding behavior (Ku et al., 2005; Delgado et al., 2008). In this regard, one should keep in mind that the joy of winning and the frustration of losing only have an indirect influence on bidding behavior. The two emotions are triggered in response to an auction outcome; therefore they occur only after the bidders have placed their bids. At the moment of placing a bid, the joy of winning or the frustration of losing can only be anticipated or expected based on the individual’s previous experience of auction outcomes. In psychological terms, the joy of winning is an immediate emotion, while the expected joy of winning is an expected emotion (Rick and Loewenstein, 2008; Adam et al., 2012).

Understanding these kinds of emotions and their role in auctions can help decipher behavioral patterns which cannot be explained by rational theory, e.g., the phenomenon of overbidding. Although the research on auctions has started to consider emotions as possible determinants of the behaviors exhibited in auctions, the mechanisms through which emotions influence the bidding process remain rather unclear. For example, Cooper and Fang (2008) reported that the expected joy of winning and spitefulness can explain the phenomenon of overbidding to some extent. In contrast, Andreoni et al. (2007) found that, at most, the expected joy of winning is only the source of the overbidding observed in 10 per cent of the cases. Goeree and Offerman (2003) did not find support for the theory of the expected joy of winning; they attribute their results to loss aversion. Delgado et al. (2008) argued that the “anticipation of the unpleasant state associated with loss”

Table 3.1.: (Selected literature on emotions in response to winning and losing an auction (JoW = joy of winning, FoL = frustration of losing). Categorization for different methods (TM = theoretical model, LE = lab experiment, NM = neuroscience methods, FS = field study, SV = survey, RV = review)

Author(s)	Focus	JoW	FoL	TM	LE	NM	FS	SV	RV
Cox et al. (1988)	FPSB auctions	X		X	X				
Ariely and Simonson (2003)	online auctions	X					X	X	
Goeree and Offerman (2003)	SPSB auctions	X		X	X				
Morgan et al. (2003)	single-unit auctions	X		X					
Ding et al. (2005)	reverse auctions	X	X	X	X			X	
Ku et al. (2005)	online charity auctions	X					X	X	
Ockenfels and Roth (2006)	auctions in general	X							X
Andreoni et al. (2007)	FPSB and SPSB auctions	X		X	X				
Fliessbach et al. (2007)	competitiveness in general	X			X	X			
Cooper and Fang (2008)	SPSB auctions	X		X	X				
Delgado et al. (2008)	FPSB auctions	X	X		X	X			
Malhotra and Bazerman (2008)	auctions in general	X							X
van den Bos et al. (2008)	FPSB auctions	X	X	X	X				
Kogan and Morgan (2009)	securities auctions	X		X	X				
Malhotra (2010)	online charity auctions	X					X	X	
Adam et al. (2011)	auctions in general	X	X						X
Ertaç et al. (2011)	FPSB and SPSB auctions	X		X	X				
Cramton et al. (2012)	clock auctions		X	X	X				
Roider and Schmitz (2012)	FPSB and SPSB auctions	X	X	X					
Adam et al. (2012)	Dutch auctions	X	X		X	X			

and the expected frustration of losing cause participants to increase their bids (quot. by Adam, 2010).

It is important to note, however, that there are also explanations for overbidding in the literature that are not directly related to emotions. Cox et al. (1988) introduced a model of CRRA that provides a partial explanation of why bidders place bids above the risk neutral RNNE bidding strategy derived by (Vickrey, 1961). However, Kagel (1995, p. 525) argued that "risk aversion is one element, but far from the only element, generating bidding above the RNNE" (quot. by Adam, 2010). Engelbrecht-Wiggans and Katok (2009, p. 82) explicitly tested the CRRA model against an emotion based regret model in a laboratory experiment and found "virtually no support for CRRA," but strong support for their regret model (quot. by Adam, 2010). These findings are also in line with our results presented in Chapter 2. An alternative explanation for overbidding in auctions is that bidders "might feel a bit like already owning the item" and therefore are willing to place higher bids (Ehrhart et al., 2008, p. 3).

By recording physiological measures during FPSB auctions, we aim to apply psychophysiological methods to the field of auction research to develop a better understanding of how bidders actually experience the outcome of an auction. This can contribute to more sophisticated economic models that incorporate the emotions of bidders in their utility functions.

3.3. Design and Method

We employed Smith's induced value theory in our study and real monetary payoffs for all the bids placed (cf. Smith, 1976). Subjects were initially endowed with 100 MU. Throughout the experiment they accumulated profits (and potential losses) from bidding in the auctions. After the end of a session, the final balance of the experimental accounts was converted into euros at an exchange rate of €0.03/MU and paid out in cash to the respective participants. The experiment described in this chapter was initially designed to analyze the impact of different informational feedback mechanisms with regard to the bidding behavior of participants in FPSB auctions. The results regarding the different feedback have been reported in Chapter 2. This Chapter presents the physiological responses to the events of winning and losing for all subjects that were recorded in the same experiment. Since the analysis in this chapter covers all subjects similarly the Auction Process and Procedure will be described here in more detail.

3.3.1. Treatment Structure

Core elements of the study design were inspired by an experiment carried out by Engelbrecht-Wiggans and Katok (2008). However, some changes to their original set up were made in order to facilitate the analysis of the physiological parameters. The main difference was that in the experiment conducted by Engelbrecht-Wiggans and Katok (2008, p. 812), a subject's bid was automatically submitted in ten consecutive auctions with independent valuations and bids of the competing computerized bidders. While that design is supposed to speed up learning "by experiencing a large number of auctions", we were interested in the immediate emotional response to an individual auction result rather than a reaction to an average of several past outcomes. Thus, in our experiment, the subjects submitted individual bids in each auction. Moreover, in the physiological measurements, we sought to reduce the noise caused by the body movements of the participants in handling the keyboard and mouse as they entered bids. Therefore, we restricted the bids (of both humans and computers) to integers and our participants only had a mouse but no keyboard to operate the software. Bids were submitted by clicking on the button that represented the respective integer amount. In detail, each subject took part in a series of 50 FPSB auctions with two computerized competitors. The auction process is depicted in Figure 3.1.

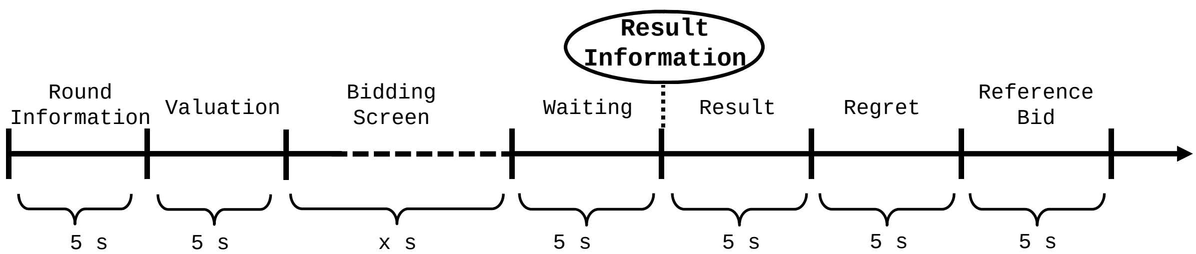


Figure 3.1.: Illustration of the auction process with the result information being displayed at 'Result Information'

3.3.2. Auction Process

In every auction, the human bidder and the two computerized bidders each received an individual valuation v_i for the item being sold in the auction. Each bidder i then submitted a bid b_i. The bidder who submitted the highest bid made a profit $\Pi_i = v_i - b_i$.[2] A losing bidder made a profit of zero. In each auction, the computerized agents were assigned independently drawn valuations from a uniform distribution with support on the integer set {0 MU, 1 MU, 2 MUs, ..., 100 MUs}. Like in the experiment carried out by Engelbrecht-Wiggans and Katok (2008), the human bidders received one of only five distinct valuations from the set {50 MUs, 60 MUs, 70 MUs, 80 MUs, and 90 MUs} in each auction. Moreover, each human bidder was assigned each of these valuations exactly ten times in consecutive auctions, i.e., a human bidder had the same valuation in auctions 1 to 10, in auctions 11 to 20, and so on. Only the order of the five valuation levels was randomly permutated from bidder to bidder.[3] This auction mechanism was explained to the participants in a previous instruction. The participants knew that they bid against computerized agents and were told that the computerized agents were programmed in a way that would maximize their expected earnings if they bid in an auction with two other identically programmed computers. A bidding function was implemented, in which the computers bid $2/3v_i$, rounded to the nearest integer.[4] Due to the asymmetry of the valuations, if a human bidder were to maximize his or her expected payoff, then he or she would win about half (51 per cent) of the auctions.[5]

[2]If the human participant's bid came to a tie with the high computer bid, the human bidder won the auction (see Neugebauer and Selten (2006) for a similar procedure). The advantage of this approach compared to breaking ties at random is that the outcome of any auction can be clearly classified in terms of the regret of the human bidder: If the human loses the auction, he or she will usually experience loser regret (no regret if the computer's bid equals the human bidder's valuation), no regret in the case of a tie and winner regret if the human bidder's bid is strictly larger than the opponents' bids. This is less clear with a random tie breaking rule.

[3]Note that this is slightly different from the design of Engelbrecht-Wiggans and Katok (2008).

[4]Strictly speaking, the symmetric risk-neutral equilibrium with the given discrete valuations and integer bids would have been $[2/3v_i]$, where $[x]$ denotes the largest integer not exceeding x. To the authors' knowledge, there is neither a general formula for bidding equilibria in discrete FPSB auctions, nor a compact analytical proof for our case. We verified the equilibrium conditions on a complete numerical evaluation.

[5]Given the implemented strategy of the computerized opponents and the tie breaking rule which favors the human bidder, the best (risk-neutral) response by the human bidders were $b(50) = 33$, $b(60) = 39$, $b(70) = 47$, $b(80) = 53$, $b(90) = 59$.

3.3.3. Procedure

In order to investigate the participants' emotional activation, the "mobile Body % Mind Monitoring System" was used (Gharbi et al., 2008). Over the course of the experiment, the participants' skin conductivity was recorded with a constant current amplifier measurement system and Ag/AgCl electrodes. The electrodes were attached on the thenar and hypothenar eminences of the palm of the non-dominant hand with standard electrodermal activity electrode paste (Boucsein, 1992). Following the recommendations of Schmidt and Walach (2000), each session started with an initial five minute rest period for calibration. All of the sessions were conducted in spring 2010 with an average room temperature of 25°C (77°F). These values are within the methodological recommendations of the Society for Psychophysiological Research (Fowles et al., 1981). The HR was derived from an electrocardiogram recording device using a lead I method with single use electrodes placed on the left and right wrist (Berntson et al., 2007). After every auction, a prompt on the computer screen informed the bidder of whether or not he or she had won the auction. In order to allow for analyzing the physiological responses and distinguishing the physiological effects of bidding and being informed of the result, the auction outcome was revealed only six seconds after the bidder had placed his or her bid. As mentioned before, the participants' interactions with the experimental system were limited to mouse inputs (Adam et al., 2011). In order to avoid measurement artifacts due to background noise, all the participants were equipped with earmuffs.

As described in Section 2.3.3 the experiment was conducted at the KIT. The software interface was implemented using z-Tree (Fischbacher, 2007) and the information regarding the point in time (in milliseconds) that the auction outcome was revealed to a bidder was written into a separate log file by the experimental system so that the behavioral data could be linked to the physiological measurements. The ORSEE software environment was used to recruit participants from a pool of university students (Greiner, 2004). A total of 78 (19 female and 59 male) subjects participated in 13 sessions with 6 subjects each. Each session lasted for approximately 1.5 hours. The average payment was €19.82, with the minimum and maximum payment in the amount of €12.30 and €23.01, respectively. After the instructions were read to the participants, they had to complete a quiz of four to five questions regarding the auction mechanism before they were allowed to start with 3 practice auctions, which were then followed by the actual series of 50 auctions. Due to a failure in comprehension, one (1) subject had to be removed from the dataset. In one session, the physiological measurements failed to operate and therefore 6 participants had to be excluded from the physiological analyses. Moreover, 12 additional participants had to be removed from the skin conductance dataset because their values were either outside the range of the measurement system or because they did not show any physiological response (non-responders). This is a common problem when measuring skin conductance (Boucsein, 1992; Dawson et al., 2007). With respect to the HR, the measurement results of 5 subjects had to be removed from the data sample because of too much noise on the signal. Consequently, the dataset contains 59 measurements for skin conductance and 66 for HR.

3.3.4. Measures

The intensity of the emotional response was assessed by analyzing the skin conductance data. In the analysis, we investigate the impact of different auction outcomes on the intensity of the physiological response. The SCR.amp was calculated for every bidder subsequent to each of the 50 auction outcomes. Data treatment with respect to SCR.amp was done analogously to Section 2.3.4. Additionally, in order to get a better account of how strong the result information is actually processed, the data was normalized.[6] This is suitable as we are especially interested in the quality of joy of winning and frustration of losing. Also the measured values for the retrieved for SCR.amp data vary greatly between individuals. Therefore the normalization facilitates an interpersonal analysis of the data. For the normalization, each of the measured values is divided by the subject's individual average SCR.amp in response to the event of being informed of their valuation. Also, to some extent, considering only the relative change of the SCR.amp also allows to control for differences in individual sympathetic activity with respect to the response to new information on the computer screen We then computed the average SCR.amp value for each bidder for the event of winning and losing an auction. Skin conductivity is directly innervated by the sympathetic branch of the autonomous nervous system (ANS) (Wallin, 1981), which provides important insight into the intensity of immediate emotions. However, it does not provide any information regarding the valence of the emotion, i.e., whether the subject regards the emotion as positive or negative.

[6] We thank an anonymous reviewer for pointing this out.

In contrast, the heart is also innervated by the parasympathetic branch of the ANS (Berntson et al., 2007). The parasympathetic activation subsequent to sensory intake is usually reflected in an initial deceleration in HR, in which negative stimuli typically elicit the strongest deceleratory responses (Bradley et al., 2008). Analyzing phasic changes in HR allows an evaluation of the perceived valence of external stimuli. Thus, the aversive event of losing an auction should result in a more pronounced drop in HR than winning an auction. We follow the recommendations of the Society of Psychophysiological Research (Jennings et al., 1981) for assessing HR by measuring the time between the successive R-waves (i.e., the inter-beat intervals) in the electrocardiogram. This approach provides an accurate measure of HR, which is indispensable in analyzing the phasic changes in the signal. The HR for each bidder and every auction is referenced to the HR at the moment that the auction outcome was revealed. Additionally, we assessed demographic factors such as age and sex.

3.4. Results

Our analysis focuses on the bidders' physiological reactions to different auction outcomes. In particular, we investigated whether winning or losing an auction is more strongly reflected in the physiological data. Before looking at the physiological data, results for bidding behavior are presented.

3.4.1. General Bidding Behavior

Each subject participated in a series of 50 auctions with two computerized opponents. A total of 82.6 per cent of the auction outcomes were efficient, i.e., won by the bidder (human or computerized) with the highest valuation; inefficient outcomes of 17.4 per cent were due to overly defensive (3.2 per cent) and overly aggressive (14.2 per cent) bids placed by the human participants. Figure 3.2 depicts all of the bids placed by the 77 participants.

Most of the bids (3,020 of 3,850 bids, or 78.4 per cent) were placed within the (risk averse) range of two thirds of the bidder's valuation and his or her actual valuation. Hence, the participants bid somewhat more aggressively than the theoretical risk-neutral Nash equilibrium of a standard FPSB auction. This is also reflected in the fact that 2,298 (59.7 per cent) of the 3,850 auctions, i.e., slightly more than the risk-neutral

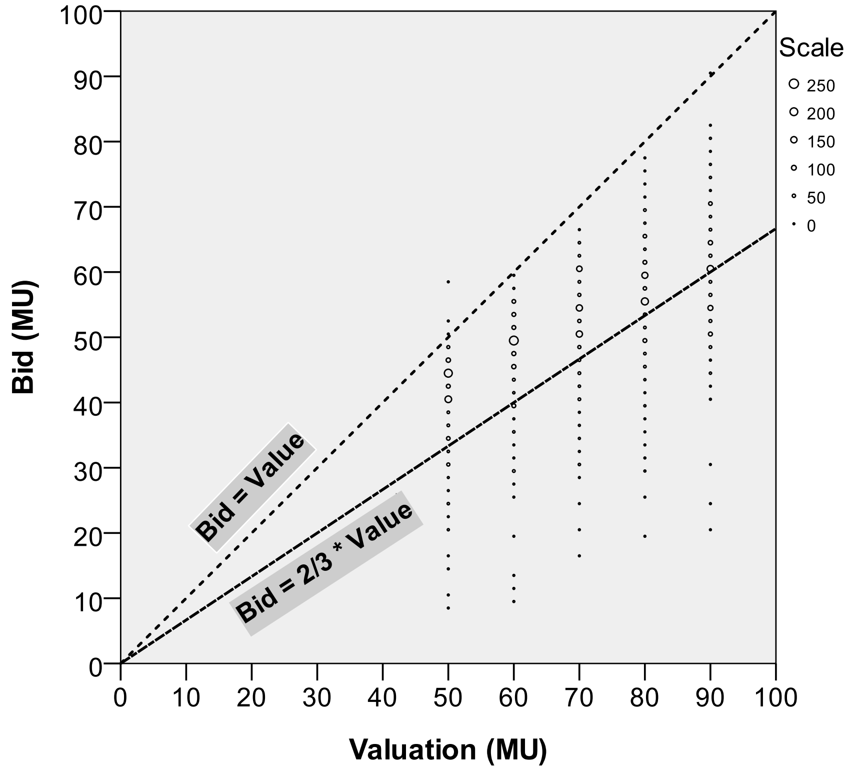
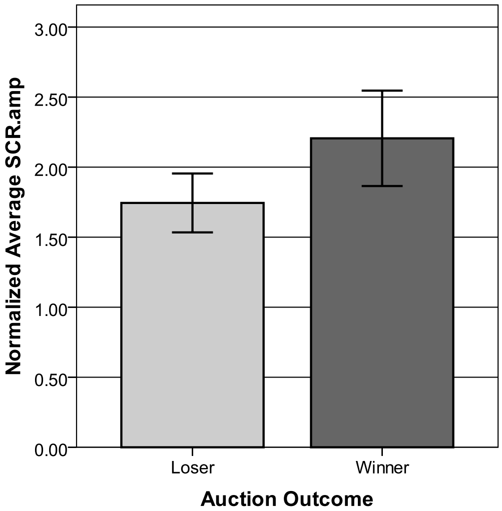


Figure 3.2.: All Bids Placed by the 77 Human Participants for the Induced Valuations {50, 60, 70, 80, 90}. The Top Line Shows all the Points where the Bids equal the Valuations. The Bottom Line shows the Theoretical Optimal RNNE in a Standard FSPB Auction with Three Bidders

best-response benchmark (51 per cent; see Section 3.3.2), were won by humans. A balanced ratio of the two possible auction outcomes is necessary for a valid physiological examination since the bidder may expect both outcomes equally. On average, human participants bid 50.90 MU, which corresponds to an average bid/value ratio of 72.7 per cent. This is consistent with the ratio observed by (Engelbrecht-Wiggans and Katok, 2008).

3.4.2. Emotional Intensity of Winning and Losing

The normalized, average SCR.amps are depicted in the left bar chart in Figure 3.3. The bar chart indicates that the physiological response to winning an auction is stronger than the respective response to losing an auction. A paired sample two-sided t-test



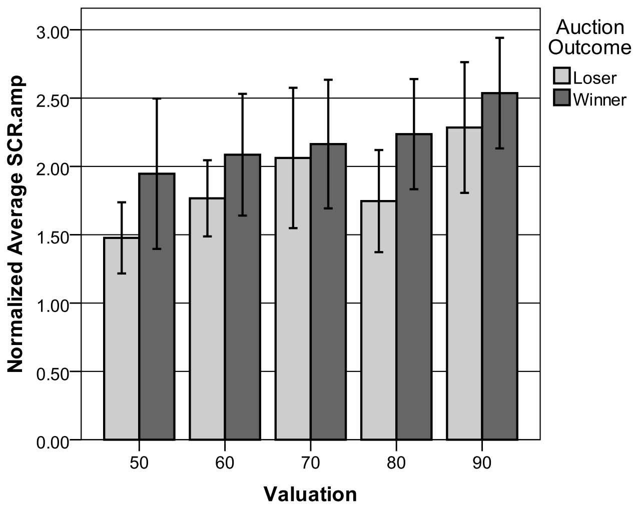


Figure 3.3.: The Left Bar Chart shows the Normalized Average SCR.amp in Response to the Auction Outcome. The Right Bar Chart indicates the Normalized Average SCR.amp in Response to the Auction Outcome for Different Valuations {50, 60, 70, 80, 90}. The Bars Represent a Confidence Interval (CI) of 95 Per Cent

shows that the difference in SCR.amp for different auction outcomes is significant (1.744 vs. 2.206, $n = 59$, $t = -3.543$, $p < .001$). At first glance, this is a somewhat surprising result since rewarding and aversive stimuli are usually reflected in the SCR.amp in a similar way (Lang et al., 1993)). We will return to this result in the discussion. In order to gain a more fine-grained insight into the physiological data, we now take into account the assumption that the emotional intensities experienced may also be subject to the valuation of a bidder or his or her respective nominal payoff. For the 5 possible valuations, it can easy be controlled for, since they were induced by the experimental design. We take the normalized data for each bidder once again and compute an average SCR.amp for whether the auction was won or lost. However, this time we calculate the average SCR.amp for each subject and each valuation for both the auctions won and lost. This results in ten average SCR.amp values for each bidder.[7] The right bar chart in Figure 3.3 depicts the normalized average SCR.amp in response to winning and losing an auction for the five different valuations. The figure shows that the measured SCR.amp is stronger if an auction was won compared to when an auction was lost and that this

[7]Some of the bidders did not win (or lose) an auction for a specific valuation; in these cases, it was not possible to compute ten average SCR.amp values for the bidders. Therefore, those specific cases were omitted in the subsequent analysis.

result holds for each individual valuation. Remarkably, the emotional intensities seem to become stronger as the valuations increase. In order to test the statistical significance of this result, we use an OLS regression with adjusted standard errors for clusters in subjects. The results of the regression are summarized under the first average SCR.amp section in Table 3.2. Additional robustness checks can be found in Appendix .

Table 3.2.: Regression Models for Normalized Average SCR.amp in Response to Winning and Losing and for Varying Valuations and a Varying nominal Payoff ($n = 576$; Standard Errors adjusted for 59 clusters in subject)

	Dependent variables							
	Average SCR.amp				**Average SCR.amp**			
Independent variables	**B**	**SE**	***t*-Stat**	**Sig.**	**B**	**SE**	***t*-Stat**	**Sig.**
dummy_winner	.326	.154	2.119	*	.418	.159	2.626	*
value_class	.137	.051	2.705	**				
avg_nominal_payoff					.026	.008	3.327	**
auction_sequence	-.125	.049	-2.579	*	-.136	.049	-2.782	**
c (constant)	1.844	.194	9.475	***	1.568	.153	10.216	***

* $p < .05$, ** $p < .01$, *** $p < .001$

A regression analysis is done for each bidder's normalized average SCR.amp on the auction outcome (dummy_winner) and the value class (value_class). Moreover, we check for mitigation effects of SCR.amp over time by taking into account the sequence in which a bidder was endowed with the different valuations (auction_sequence).[8] The results of the regression reveal that both the auction outcome (winner or loser), as well as the different valuations (50, 60, 70, 80, 90), have a significant influence on the SCR.amp. While this result may lead to the conclusion that higher valuations per se result in increased physiological responses, this effect could actually also be triggered by the nominal payoff, which is also higher for higher valuations.[9] In this chapter, we define the nominal payoff p_i as the amount of money a bidder i would get if his or her bid b_i was successful, that is, $p_i = v_i - b_i$. Thus, in contrast to the profit Π_i, the nominal

[8]In the regression, the five different valuations are encoded as value classes 0 (the valuation is 50), 1 (60),. . . 4 (90). Analogously, the auction sequence number is encoded by the values 0 to 4, i.e., for the first valuation that a bidder has in the experiment, the variable auction_sequence is set to 0, for the second valuation it is set to 1, and so forth.

[9]Note that avg_nominal_payoff and value_class are highly correlated at Pearson's $r = .799$, $p = .001$. Apparently, by the experimental design, higher valuations usually result in higher realized payoffs. Due to the high correlation, the two values cannot be analyzed simultaneously in the regression.

payoff p_i is independent of whether the auction was actually won or lost. The second average SCR.amp section (on the right) in Table 3.2 shows a respective analysis which substitutes the variable avg_nominal_payoff for value_class. This variable indicates the average nominal payoff a subject could have realized for the distinct valuations with the respective bids that she or he placed. The analysis shows that—similar to the variable value_class—the variable avg_nominal_payoff also influences the subjects' physiological reactions significantly; and consequently, higher nominal payoffs result in stronger responses while the rest of the results remain unchanged. We will come back to this result in the discussion.

3.4.3. Valence of Winning and Losing

Even though we identified the differences in SCR.amp upon winning and losing an auction, the valence of an emotion, i.e., whether an emotion is positively or negatively perceived by the subject, is typically more clearly reflected in the phasic changes in HR (Lang, 1993). Figure 3.4 depicts the change in the average HR in response to the auction outcome. The left graph shows the time period of up to 6 seconds after the auction outcome. The blue line depicts the change in average HR after losing an auction. At its peak, the drop in HR is significantly stronger than the drop in HR subsequent to receiving the valuation information. This provides evidence that the auction outcome does, in fact, lead to a strong physiological reaction. The bars in the graph on the right of Figure 3.4 represent the 1.0, 1.5, and 2.0 seconds subsequent to when the auction outcome was revealed. This indicates that the deceleratory response in HR is stronger for losing than for winning. Moreover, one can observe that the subsequent acceleratory response, which is a proxy for the activity of the sympathetic nervous system, is stronger for winning. Thus, while both shapes of the heart waves have a triphasic pattern (deceleratory, acceleratory, deceleratory), they are clearly distinguishable.

Table 3.3 depicts a set of paired sample t-test results ($n = 66$) for the mean difference in phasic changes in HR in response to the auction outcome. We test whether the event of losing induces a stronger deceleratory response than the event of winning for different time periods after the auction outcome. The analysis reveals that the HR is significantly lower in response to losing an auction compared to winning an auction just 1.4 seconds after the auction outcome is revealed. This result is similar to the responses documented in the psychological literature regarding the phasic changes in HR when

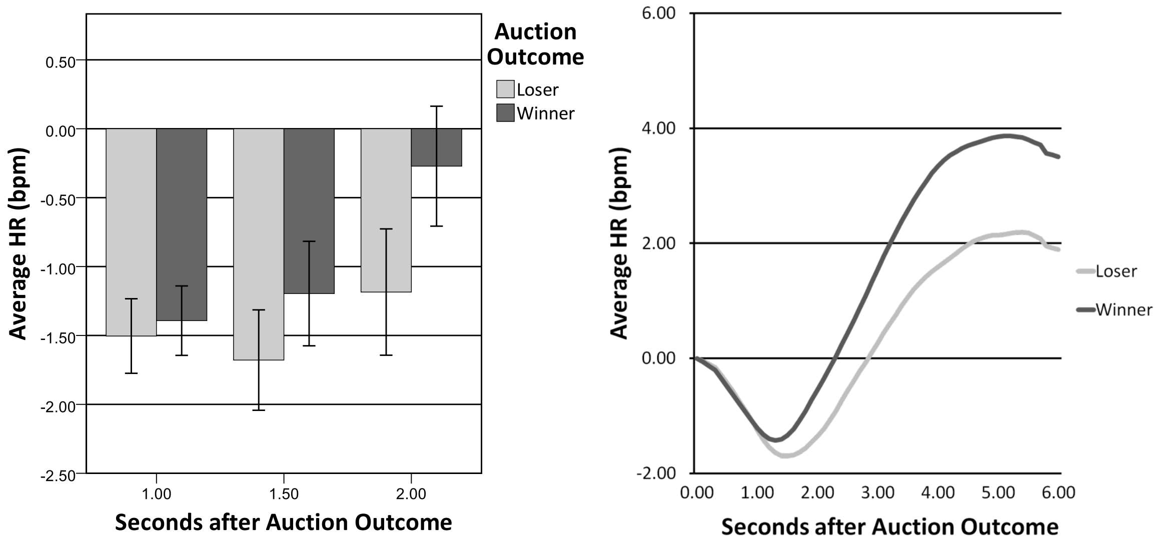


Figure 3.4.: Phasic Changes in HR in Response to Auction Outcome. The Left Graph Shows the Typical Triphasic Waveform for Up to Six Seconds. The Bars in the Right Chart Show the Response Time for 1.0, 1.5 and 2.0 Seconds Subsequent to the Auction Outcome. The Bars Represent a Confidence Interval (CI) of 95 Per Cent

viewing unpleasant pictures (Bradley et al., 2008). This is also supported by additional analyses in the Appendix B.1. It is important to note that external events with both a negative and a positive valence generally induce a deceleratory response. However, the initial deceleratory response is usually stronger for events with a negative valence (Bradley et al., 2008). The stronger deceleratory HR response after an auction has been lost may indicate that losing an auction is processed similarly to other negative events. For example, Osumi and Ohira (2009) found a similar drop in HR as an immediate reaction to receiving subjectively unfair offers in an ultimatum game. Adam and Kroll (2012) reported a stronger drop in HR as a reaction to losing a high stakes lottery in comparison to winning a high stakes lottery. Ravaja et al. (2006) found an initial drop in HR as a reaction to negative events in video games and Hubert and de Jong-Meyer (1990) reported similar HR patterns as a reaction to watching movies with negative content (see also Palomba et al. (2000) for similar results). In summary, our interpretation of the HR pattern observed in our study is that losing a FPSB auction induces a negative emotion, which we refer to as the frustration of losing.

Table 3.3.: Analysis of Phasic Changes in HR in Response to Winning and Losing ($n = 66$)

Seconds after Auction Outcome	**Average Difference in HR (lose-win)**	***p*-value**	**Sig.**
1.0	-.11	.500	
1.1	-.21	.227	
1.2	-.23	.191	
1.3	-.30	.115	
1.4	-.41	.034	*
1.5	-.48	.014	*
1.6	-.59	.004	**
1.7	-.79	.002	**

$^{*}\ p < .05$, $^{**}\ p < .01$, $^{***}\ p < .001$

3.5. Discussion

3.5.1. Limitations and Future Research

When classifying our results into the previously presented auction literature, we have to state that concepts such as "joy of winning" or "frustration of losing" are typically modeled for utility functions which aim at explaining subjects' bidding behavior and their decision processes in anticipation of the submitted bid. Therefore, it is important to note that our experimental setup is only capable to assess subjects' responses after the result revelation—which we call an experienced emotion. Hence, while we find strong evidence for such an emotion in response to the auction outcome, we can neither conclude that this reaction was or was not already anticipated before submitting a bid, nor that it was already reflected in a subject's bidding process. We must also acknowledge that our FPSB auction design differs from the experiment of Engelbrecht-Wiggans and Katok (2008) due to our objective to assess physiological parameters. In particular, we restricted human-computer interaction to mouse inputs, the subjects had to submit individual bids in each auction, and we introduced constant time lags between the revelation of successive information on the valuation, the bidding process, and the auction outcome.[10] Therefore, our economic results are consistent but not perfectly comparable with Engelbrecht-Wiggans and Katok (2008). As outlined in the results section,

[10] Also the experimental instructions were slightly different (see Appendix A.1).

examining subjects' sympathetic activation shows that winning an auction elicits significantly stronger physiological responses than losing an auction. This is remarkable since both pleasant and unpleasant stimuli are usually reflected in similar SCR.amps. Bradley et al. (2008), for example, did not observe statistically significant differences in average SCR.amp of subjects in response to negative (e.g., hospitals tombstones in a cemetery or) and positive stimuli (e.g., pictures of families or flowers). Dawson et al. (2011) concluded that SCRs occur in the anticipation of particularly aversive significant outcomes that are related to decision making. In this light, the stronger physiological response to a positive auction outcome compared to a negative auction outcome is even more surprising. But also from an economic perspective, one would expect more intense physiological reactions to negative economic events. For example, it is well known that subjects reveal loss aversion decision patterns in many circumstances. Goeree and Offerman (2003) found support for loss aversion, which explains their auction data. This leads to the conclusion that subjects are more sensitive to negative feedback information and therefore exhibit higher emotional arousal when losing an auction. However, our results do not support this notion. To the contrary, our data suggests that the physiological reactions generated by the joyous event of winning an auction are more dominant than when losing an auction. A first simple explanation for why losing an auction is not as arousing as winning could be that in our setting a bidder never actually loses money when he or she loses a FPSB auction. Rather, he or she only loses the opportunity to make a profit.[11] Therefore, it is possible that the forgone gain does not affect subjects as intensely as a real loss of money. Still, the drop in HR indicates that participants are not emotionally indifferent to losing a FPSB auction. A second explanation might be that subjects are well aware of being one of three participants in the auction. Potentially, they falsely expect to be the winner in only one third of the auctions, which is not the case since they have higher valuations than the computerized bidders. Being exposed as the "winner" is therefore more unexpected and more arousing because of this. Even though the electrodermal response to losing is weaker compared to winning an auction, the response is still remarkable and the decelerated HR is an indicator of the negative emotional valance that is associated with losing an auction. A third explanation could be that subjects attempt to regulate their negative emotions in

[11] The subject could actually make a negative payoff when placing a bid that exceeds a bidder's own valuation. This behavior, however, is clearly irrational and almost never occurred in our experiment.

our experimental context-and therefore do not express or reappraise them. The Emotion Regulation Questionnaire (ERQ) (Gross and John, 2003) and measuring subjects' heart rate variability (cf. Fenton-O'Creevy et al., 2012) serve as measures for conscious and sub-conscious emotion regulation (ER). These measures could be used in future research to investigate the moderating role of ER on subjects' physiological responses to winning and losing. While ER, is beyond the scope of this study, it will be further examined in the following chapters. Even though we have evidence that the experience of winning an auction results in a significant physiological response, one cannot completely rule out the alternative explanation that subjects primarily react to the amount of money won instead of experiencing a "joy of winning" as an emotion completely independent of the monetary payoff. Below, in the future research section, we propose an experimental design that is suitable to systematically investigate this particular question. Bidders' increasing physiological reaction to higher valuations and higher nominal payoffs is another interesting result. We observed that higher induced valuations go along with stronger emotional responses, regardless of whether the subject wins or loses the auction. However, we also observed that higher nominal payoffs also resulted in increased physiological reactions. The outcome of an auction induces higher emotional arousal when valuations or the nominal payoffs are higher. This pattern may have two explanations: First, bidders may be more aroused when the probability of winning and the expected payoff is higher; and second, bidders may be more aroused in response to realizing higher payoffs or higher foregone payoffs. Finally, a combination of both effects also seems plausible. In summary, with the current experimental design it is not possible to distinguish whether the bidders' SCR.amps are higher for higher value classes (1) because the expected payoff is higher, or (2) because the nominal payoff is higher, or (3) both. In terms of future research, it may be interesting to clarify this effect further by systematically varying the amount of the nominal payoff and the probability of winning. In any case, the results of our experiment show that higher payoffs—expected or realized—induce stronger intensities of joy when winning an auction. This result contradicts the theory that there is a joy in winning regardless of the monetary payoff (van den Bos et al., 2008). In fact, higher nominal payoffs also induce stronger SCR.amps when a subject loses an auction. This pattern could be explained by taking loser regret into account (cf. Chapter 2). The SCR.amps are more likely to increase with the amount of the valuation even in the case of losing because the subject feels that he or she has just lost the opportunity to receive a considerable payoff. Therefore, we contradict the notion that the emotion in response to winning or losing the auction is independent of the monetary consequences of an auction (van den Bos et al., 2008). On the contrary, it seems that the size of the nominal payoff significantly influences the intensity of the emotional response. This explanation corresponds with the regret theory, which suggests that decision makers react emotionally to missed opportunities by comparing actual outcomes with other possible outcomes (Humphrey, 2004). An alternative explanation according to Delgado et al. (2008) assumes that the frustration of losing the social competition increases with the amount of the valuation. This explanation is in line with previous research that was done on competitive arousal and auction fever. For instance, Ku (2008) showed that bidding behavior in a dollar auction is more aggressive if the stakes are high. Even though the causes of the emotional reactions documented in this study have not been fully explained yet, we conclude that applying a psychophysiological methodology in the area of auction research provides a promising approach for deciphering emotions within the context of market decision making.

The emotions related to winning and losing are what distinguish auctions from that of fixed price offers on retail sites. According to Stafford and Stern (2002, p. 139), these emotions provide the basis for the "game-like action and bidding frenzy characteristic" of auctions (cf. Adam, 2010). To this extent, we presented an experiment that uses physiological measures to directly assess correlates of the bidders' emotional processing in FPSB auctions. Our results show that the bidders, in fact, have distinguishable physiological reactions in response to the auction outcome, namely that the event of winning an auction is processed much more intensely than the event of losing. Moreover, we provide physiological data which suggests that bidders indeed experience an aversive emotion in response to losing an auction. The event of losing an auction induces a deceleratory cardiovascular response, i.e., a phasic decrease in HR. While the deceleration is stronger for the event of losing an auction, the subsequent acceleration is stronger for the event of winning an auction. The frustration of losing the auction competition or experiences of regret are potential explanations for the aversive emotion triggered. In summary, we conclude that auctions either convey an aversive (frustration of losing) or a rewarding (joy of winning) emotion. In this regard, our data shows that the joy of winning in FPSB auctions results in stronger reactions than the frustration of losing. It is notable that this result is even robust for all five distinct value classes. This characteristic is presumably an important contributing factor in making online auctions "one of the greatest success stories of web-based services" (Ariely and Simonson, 2003). In an auction, a bidder can experience the "uniqueness of being first" (Ku et al., 2005; Adam, 2010). Pronouncing the joy of winning on auction platforms could be one way of generating an intense positive shopping experience, which could potentially lead to the temptation of trying to "win" another auction. Conversely, pronouncing the event of losing an auction on a platform may also increase the excitement of bidders. Our physiological data indicates that losing an auction is in fact associated with a negative valence of significant intensity. Therefore, the bidders will try to avoid this "aversive" emotion (Frijda, 1986) and might even place higher bids the next time they participate in an auction. The findings of our experiment also result in a number of questions for further research. It is important to point out that in our experiment the human participants compete with computerized bidders. Thus, there is no interaction with other human subjects. However, Bosman and Riedl (2004, p. 3) argue that interacting with other human bidders can cause "emotional spillover effects between subjects," such as feelings of anger and envy (see Adam, 2010). For instance, Bault et al. (2008) showed the subjects' physiological processing during lottery decisions is already affected by the mere presence of another human agent, even though there is no strategic interaction from a game theoretical perspective. With regard to feelings of joy and frustration in auctions, it would therefore be interesting to analyze the extent to which the intensities change when the bidders face human competitors. For instance, it may well be that the frustration of losing is even stronger than the joy of winning when human competitors are involved. Another approach for investigating the boost of the frustration of losing would be to introduce bidding fees to the auction. With this approach, a real monetary loss occurs when the participant is not the highest bidder, which could lead to more intense physiological reactions when losing an auction. Moreover, the experiment focuses on FPSB auctions, i.e., static auctions in which only a single bid can be submitted by each bidder. However, the phenomenon of auction fever, a prominent example of the impact that emotions can have on bidding behavior, has mainly been observed in dynamic auctions (Ockenfels et al., 2006; Adam et al., 2011). With auction fever, Adam (2010) notes that the bidders' "adrenaline starts to rush, their emotions block their ability to think clearly, and they end up bidding much more than they ever envisioned" (Murnighan, 2002, p. 63). According to Haruvy and Leszczyc (2010) this is "induced by the dynamic interaction among bidders in an ascending bid auction" (Adam, 2010). Accordingly, future research in the field of auctions should also focus on how the joy of winning and the frustration of losing are experienced in dynamic auctions. This way, the physiological responses of bidders in static auctions can be directly compared with those in dynamic auctions.

Contrary to these integral emotions that evolve within the auction, the next chapter will examine the influence of emotions which are completely incidental. These affective states are not related to the auction task whatsoever, and can be triggered for instance by the use of images. Thereby we also assess participants' emotion regulation strategies.

Chapter 4.

Affective Images, Emotion Regulation and Market Behavior

Chapter 3 and 4 dealt with the influence of integral emotions i.e. emotions elicited due to the auction mechanism. However, auction platforms also employ methods to trigger emotions which are not originated by the mechanism itself. Electronic marketplaces, such as Internet auction platforms, frequently employ images as design elements on their websites. This might be done in order to either induce a sense of community or competition among the market participants. In this chapter, we investigate the impact of such affective images on bidding behavior in a controlled psychophysiological laboratory experiment during which participants' affective processes are assessed through psychophysiological measurements. Immediately before placing a bid in a FPSB auction, bidders are presented: a) competitive sports scenes, b) families or children, or c) a blank screen. Although participants report not to be affected by the images, we find that the images significantly shape their bidding behavior. This relationship is mediated by the bidders' emotional state and it is moderated by the bidders' emotion regulation strategy. Our results entail valuable insights about the coherence of emotional stimuli on marketplaces and users' decisions. They also question recent strategies by market players.

4.1. Introduction

"It's better when you win it!" advertised eBay in its commercial campaign "Shop Victoriously" (eBay.com, 2007). In the campaign, bidding in an eBay auction was compared to sports events such as football matches and dog races. Thereby, the world's largest consumer online auction site directly addressed the emotions the bidders experience on their platform by the use of exciting images (Adam, 2010). Other online market platforms, such as DubLi.com, use images of smiling couples or children-like avatars in order to increase the warmth and social presence during users' shopping experience. These examples hint at a strategy of auction and fixed-price retail platforms, which embed affective images in their websites in an effort to maximize revenues. While there is evidence that the display of affective images in fact alters subjects' emotional processing and perception (Hassanein and Head, 2007; Zahedi and Bansal, 2011), little is known about how the users' actual decision making process in such information systems is directly or indirectly affected.

In this chapter, we conduct a psychophysiological experiment to investigate whether displaying affective images to the participants of electronic auctions has an influence on the bidders' emotions and decision making. As the underlying market institution we consider a FPSB auction, in which each bidder submits a single bid. The bidder who has placed the highest bid obtains the item and has to pay the amount of his or her bid (Vickrey, 1961). Before every auction, the subjects are shown affective images that induce either a sense of competition (through images depicting sportsmen) or a sense of community (through images depicting families or children), or, as a control, a blank screen is shown. Bidders' affective reactions to the images are assessed through SC and HR measurements, which are well-known psychophysiological correlates of human emotions (Bradley et al., 2008; Dawson et al., 2011; Riedl et al., 2010). In this vein, we are able to continuously assess bidders' affective processes, which would not have been feasible by the usage of questionnaires alone. These measures enable us not only to assess the bidders' emotional processing when seeing the affective images, but also how the bidders regulate these emotions on an individual level. According to the concept of emotion regulation, subjects deal with emotional stimuli in various ways and follow specific strategies, e.g., reappraisal or suppression (Gross and John, 2003). Previous research has shown that subjects' emotion regulation strategy impacts their response to affective cues and also their decision making. In the following, we investigate these processes in the context of electronic markets.

In a nutshell, our results reveal that affective images, although they are unrelated to the task, systematically influence the users' emotional processing and behavior. Even in the context of electronic auctions, where real money is at stake, community and competition images induce emotions of considerable intensity with different degrees of pleasantness (referred to as valence). This in turn also impacts behavior. Bidders facing images of competitive sport events place lower bids, whereas bidders seeing community images place higher bids on average. Moreover, subjects' individual strategies for regulating their emotions mitigate or amplify their affectedness to the images. In fact, the more subjects suppress their emotions to the depicted images (i.e., try to inhibit their responsive reactions) the stronger they are biased in bidding behavior.

4.2. Theoretical Background

4.2.1. Affective Images, Social Presence and Human Computer Interaction

A central element of user interface design is the use of images (Hassanein and Head, 2006; Zahedi and Bansal, 2011). In the context of shopping websites, images are an important medium for users when they are forming attitudes and expectations about the platform as a whole or a specific product they consider buying (Song et al., 2012). Images trigger affective responses, resulting in approach or avoidance tendencies (Bradley, 2000). Thus, affect inevitably also plays a vital role in human-computer interaction. In this context, Deng and colleagues argued that affect "influences and mediates specific aspects of interaction with a user interface" (Deng and Poole, 2010, p. 711). The visual complexity and arrangement of a webpage triggers affective processes in the user, which in turn influence emotional and behavioral responses. For example, affective processes have an influence on intention to use, perceived ease of use, usability, and trust (Cyr, 2008; Qiu and Benbasat, 2009; Riedl and Javor, 2012; Zahedi and Bansal, 2011). With respect to trust and privacy, Li and colleagues found that a user's willingness to disclose personal information to an e-vendor is subject to the emotions elicited by the overall webpage impression (Li et al., 2011). Deng and colleagues showed that order design features and the visual complexity of a webpage induce affective processes that have an influence on a user's approach tendency, i.e., the willingness to further explore a website (Deng and Poole, 2010).

Marketers also have to carefully consider the influence of emotions when designing a platform. Menon and Kahn (2002) found that the pleasure induced by the initial exposure to the website of an online retailer affects a user's shopping behavior. Images are also frequently used as design elements in electronic auctions. When comparing the different platforms, the emotional states triggered on these platforms seem to fall into the following two main categories of human relationships. The first category encompasses images that induce a sense of competition or excitement. An example is eBay's advertisement campaign "Shop Victoriously," which compared successful bidding to winning a football match or dog race (eBay.com, 2007). Similarly, other auction platforms show images of customers on their website who celebrate winning an auction or cheerful avatars raising their hands in the air. The other category addresses especially images address primarily feelings of a cozy, safe familiar atmosphere. An example is the auction website DubLi.com which shows photos of couples and uses a smiling avatar to guide users. Similarly, eBay has also launched advertisement campaigns that fall into this category. For example, in a commercial that aired in December 2011, a family was shown next to their Christmas tree while doing some last minute shopping on eBay. Menon and Kahn concluded that "marketers should carefully consider the emotional impact of the initial encounter with a website since it can affect their subsequent behavior" (Menon and Kahn, 2002, p. 38). Therefore, it is important to understand if and how such social images actually affect the users' emotions and behavior.

Presumably, one reason for the use of social images is that platform operators aim at boosting their users' sense of human sociability. This stems from the observation that electronic markets are often regarded impersonal and anonymous (Hassanein and Head, 2007). The usage of social factors is usually explained by the psychological construct of social presence, which models the users' longing for physical presence of other humans (Fulk et al., 1987). Previous research specifically connected social presence with "warmth" in a sense that it reveals human warmth and sociability (Hassanein and Head, 2006). Rafaeli and Noy showed that especially images of competitors' faces increased virtual presence (Rafaeli and Noy, 2005). Also Hassanein and Head examined which features of the web interface can systematically increase the perception of social presence on websites and found human-centric images in emotional contexts to be useful (Hassanein and Head, 2007). In another study, Cyr and colleagues supported this finding: the authors implemented website conditions with varying levels of human and facial factors and found that human images with facial features can make a website more appealing (Cyr et al., 2009). In particular, users perceived the website as more appealing and more trustworthy when human images were displayed. Nunamaker and colleagues found that smiling computer avatars are perceived as more likeable than agents with a neutral demeanor (Nunamaker et al., 2011). Qiu and Benbasat showed that product recommender agents which employ humanoid embodiment can enhance social presence, which in turn positively affects the customers' perceptions and intentions (Qiu and Benbasat, 2009). Taken together, it can be stated that socially-rich images are a useful tool to induce social presence.

Research so far has primarily focused on the positive connection of social presence on the user's perceived usefulness, trust and enjoyment (Hassanein and Head, 2006). In this context, Cyr and colleagues stated that "the effect of ads depicting images of people has yet to be studied extensively, but early research on this topic suggests that images of humans do influence people's behaviors in online environments" (Cyr et al., 2009, p. 543). In summary, human images on websites can trigger affective processes that shift users' social perception. However, research on how and to what extent these images can also systematically shape the users' decision making is scant. In this study, it is our goal to examine to what degree affective images can shift decision making in electronic auctions.

4.2.2. Measuring Affective Responses

An affective process is usually triggered by an emotionally-competent stimulus, i.e., a particular object or event associated with a subjective significance (Bechara and Damasio, 2005). The emotional response then unfolds subsequently to the stimulus along the timeline. Depending on the nature of the stimulus, the emotion triggered along the affective process can be categorized as integral or incidental (Rick and Loewenstein, 2008). Images on websites can, for instance, convey essential product information and are thus an integral part of a user's cognitive and affective product assessment process. In this sense, a product image can be regarded as a stimulus that triggers an integral emotion: in addition to conveying useful product information, a product image may trigger emotions like desire or disgust. However, images can even then be inducers of affective processes, when they are seemingly unrelated to the current task. An image which is seemingly unrelated to the product can be regarded as a stimulus that triggers an incidental emotion. For instance, images used as additional design elements may trigger emotions like joy or anger. In our study, we focus specifically on incidental emotions and therefore use images that do not convey any relevant information about the auction or the good being auctioned.

The advances in cognitive neuroscience and psychophysiology have contributed to deeper insights into the cognitive and affective processes underlying human decision making. In recent years, the methods, theories, and tools from cognitive neuroscience have also gained increasing interest from IS researchers. This emerging field of IS research is commonly referred to as NeuroIS (Dimoka et al., 2012; Riedl et al., 2010; Vom Brocke et al., 2013). In this study, we use psychophysiological measures to unobtrusively assess the influence of images on the affective responses of users participating in electronic auctions. In particular, we measure subjects' SC and HR. Both measures reflect activity of the ANS and therefore cannot be directly influenced by free will. These measures are frequently used as proxies for emotional correlates in psychophysiology (Bradley et al., 2008; Dawson et al., 2011) and can help IS researchers to shed more light on the affective processes of users interacting with information systems (Cyr, 2008; Riedl et al., 2010).

Research in psychophysiology has shown that changes in SC predominantly reflect sympathetic activation in response to arousing events (cf. Lang et al., 1993). In our context, bursts of sympathetic activity, commonly referred to as SCR, are induced by the arousal inherent in affective images. Thereby, images with emotional content (irrespective of their valence, i.e. whether they are pleasant or unpleasant) typically induce a similar SCR, which is distinct from the SCR that is induced by images without emotional content. HR responses, on the other hand, reveal insight into how an image stimulus is ultimately perceived by the subject. Recent studies have confirmed that the initial cardiac deceleration, i.e., a temporary drop in HR after experiencing an external stimulus, is a proxy for subjects' experienced emotional valence, where the amplitude of the drop is negatively correlated with the valence (pleasantness) of the event (Astor et al., 2013; Bradley, 2000). The orienting parasympathetic response results in a small drop in HR for pleasant images, whereas threatening or rather unpleasant images result in a pronounced drop in HR. In order to systematically categorize affective responses which occur subsequent to appetitive or aversive stimuli, Lang developed the International Affective Picture System (IAPS) (Lang, 1995). IAPS is a database with a large set of emotionally evocative images, which are rated and standardized in terms of valence and arousal. Valence and arousal are frequently used dimensions for judgments about emotional stimuli (Russell, 1980). Previous research has shown that the IAPS images can elicit psychophysiological responses, e.g., HR response, SCR, and startle reflex (Bradley, 2000; Bradley et al., 2008). Moreover these images can easily be edited, distributed, and catalogued. Due to these characteristics, IAPS is highly validated and widely used in experimental studies.

In neurophysiological studies building on IAPS, the images are usually integral to the task, because the images and the neurophysiological responses are the actual focus of the investigation. In our study, we investigate the impact of these affective images in the context of electronic auctions. Thus, the images are unrelated to the task in our study. As outlined above, affective images with social connotations have been shown to elicit affective processes in humans (Cyr et al., 2009; Hassanein and Head, 2006, 2007). However, it is an open question whether such unrelated images can trigger (incidental) affective processes that eventually have an influence on economic decision making, i.e., influence bidding behavior in an auction task where real money at stake. Consequently, as the first building block of this theory, we hypothesize that seemingly unrelated affective images (which induce either a sense of community or a sense of competition), that are displayed before an electronic auction, can trigger (incidental) emotional processes in the bidders. The images used in this study were selected to have comparable levels of arousal. Therefore, we do not expect significant differences in SCR between the display of community and competition images. We do expect, however, that the images induce SCRs which are stronger than when no images are displayed. Moreover, according to the IAPS repository, the selected images differ in the perceived valence with community images being perceived as more pleasant than competition images. Therefore, we expect systematic differences in the bidders' HR responses when being exposed to these two categories of images. Our first research hypothesis thus states:

> **Hypothesis 3a:** *Bidders exposed to competition images experience stronger deceleratory HR responses than bidders exposed to community images.*

4.2.3. Emotional Bidding

Previous research has provided evidence that emotions can have an impact on economic decision making (Bechara and Damasio, 2005; Riedl et al., 2010; Slovic et al., 2007). With respect to images and incidental emotions, Winkielman and colleagues showed that the presentation of images with frowning or happy faces changes subjects' behavior on pouring and consumption of drinks (Winkielman et al., 2005). Similarly, Trujillo and colleagues found that subjects took riskier financial decisions when seeing images with happy faces, while they took less risky decisions when looking at angry or fearful faces. Interestingly, in both studies positive and negative expressions altered subjects' decision behavior independently of whether they stated that the images influenced them. Decision behavior was not moderated by subjects' perception of the image influence. These studies show that images seems to be capable to influence subjects' decision behavior in simple tasks, and that this influence happens unconsciously. Emotions have also been found to play a role in auction decision making (Ariely and Simonson, 2003; Ding et al., 2005; Ku et al., 2005). Ariely and Simonson found that the dynamics of auction participation require consumers to be highly involved (Ariely and Simonson, 2003, p. 116). Ding and colleagues concluded that "emotions are an integral component of a bidder's decision state and bidding strategy" (Ding et al., 2005, p.363). Based on a literature review, Adam and colleagues derived a conceptual framework for emotional bidding (Adam et al., 2011). The authors argued that a bidder's emotional state is affected by specific emotions that are integral to the task and triggered by the auction environment and the bidding process. The induced emotional state can in turn have an influence on bidding behavior. As examples for the influence of integral emotions, i.e., elicited by the auction mechanism, Ku and colleagues found that time pressure, social facilitation, and rivalry can induce a highly competitive atmosphere and high levels of arousal in the bidders (Ku et al., 2005). This "competitive arousal" can ultimately even cause bidders to place higher bids than they actually intended to. For instance, Heyman and colleagues reported that bidders place higher bids if the degree of rivalry is comparatively high (Heyman et al., 2004). With respect to time pressure, Adam and colleagues conducted a psychophysiological experiment and showed that in descending clock (Dutch) auctions the bidders' arousal levels are affected by the clock speed (Adam et al., 2012). Moreover, the authors found that the level of arousal as measured by HR mediates the influence of clock speed on bidding behavior. Evidently the mediating role of competitive arousal on decision making seems to be driven also by the auction format.

Only few experimental studies so far have examined the effects of emotions on bidding behavior. Bosman and Riedl exposed bidders to positive and negative economic shocks in FPSB auctions, in order to induce positive and negative moods (Bosman and Riedl, 2004). While the mood induction was effective, only subjects in the negative mood condition placed significantly higher bids. Subjects in the positive mood condition did not alter their decision making. However, a potential limitation of this study is that the economic shock itself can change the subjects' bidding strategy, since also the subjects' wealth is changed by the shock (see Ding et al., 2005). Thus, the emotions induced in this study are integral and not incidental as is the case for our experiment. In a more recent experiment, Capra and colleagues examined the influence of induced incidental positive and negative emotional states on bidding behavior in nth-price auctions (Capra et al., 2010).[1] It was found that subjects in the positive mood treatment generated an upward bidding bias and overbid more often than subjects in a no- or negative-mood treatment. The authors hypothesized that the positive mood might enhance subjects' competitiveness or that it lets them become less detail oriented. This result is supported by a recent study which builds on data from auction houses in London, where prices of low-priced paintings were positively correlated with good mood (Silva et al., 2012).

As will be described in more detail in the method section, for our study we employ a FPSB auction, in order to analyze the influence of social images with different emotional connotations on bidding behavior under controlled conditions. For our hypotheses development it is important to note that a bidder has to face the following trade-off when placing a bid in a FPSB auction: submitting a higher bid increases the probability of winning-however at the drawback of a smaller payoff. In contrast, submitting a lower bid decreases the probability of winning-but then again at the advantage of a greater payoff (Vickrey, 1961; Ding et al., 2005). As outlined above, we have identified two predominant strategies frequently applied by e-auctioneers to elicit (incidental) affective processes in the users. One strategy aims at increasing social presence by displaying community images. The second strategy calls on increasing the users' sense of competition. We hypothesize that bidders exposed to community images will place less risky

[1] Similar to the FPSB auction, this auction format is static in the sense that bidders submit one single bid and that higher bids increase the probability of winning. In this auction format, however, the weakly dominant strategy is to bid one's own valuation.

and therefore higher bids, while bidders exposed to competition images will place more risky and therefore lower bids. This translates into our second research hypothesis:

> **Hypothesis 3b:** *Bidders exposed to competition images place lower bids than bidders exposed to community images.*

Notice that H3a conjectures an influence of the competition and community images on affective emotional process, whereas H3b conjecture a direct influence of the images on bidding behavior. In order to provide comprehensive insight into how the images possibly affect bidding behavior, we are also interested in whether there is an indirect effect of the images on bidding behavior that is mediated by the induced emotional processes. This possible mediation is addressed in H3c:

> **Hypothesis 3c:** *The impact of affective images on bidding behavior is mediated by bidders' deceleratory HR responses.*

4.2.4. Emotion Regulation

Research has provided empirical evidence that subjects, depending on interpersonal differences, continuously regulate their emotions—and that this regulation process influences how they experience and respond to emotional stimuli. The psychological concept of emotion regulation (ER) (Gross, 1998b) stems from the assumption that humans constantly, consciously or unconsciously, regulate the emotions they have, and therefore differ in how they experience or express their emotions (Gross, 1998a; Lerner et al., 2004).

In particular, individuals differ in their ER capabilities and the applied ER strategies are determined by personality traits and psychological capacity (Gross, 1998b). Gross developed an ER process model in which emotions unfold over time and are generated in an evolving process (Gross, 1998b). The author distinguished between antecedent and response-focused ER strategies.[2] Antecedent ER strategies apply while the emotion is

[2] Previous to the ER definition by Gross, similar concepts have been introduced, e.g. on coping, mood regulation, and traditional ego-defenses. Emotion regulation, however, has been clearly distinguished from them (Gross, 1998b). Other approaches from clinical psychology also cover additional ER techniques such as acceptance, avoidance, problem-solving, and rumination (Aldao et al., 2010). Moreover, there are approaches that also focus on the non-conscious mechanisms of ER (Williams et al., 2009). However, in the field of ER and decision making Gross's model is the most prominent.

still unfolding and has not reached its peak. The major representative for antecedent-focused ER strategy is reappraisal. Consider for instance the user of an online auction platform, who is interested in a second-hand car. In one of the advertised auctions the user finds an appealing image of a suitable car, next to relevant technical information. When applying reappraisal, the user would try to avoid becoming overly excited when looking at the image about the prospective new car; for example, by focusing on technical details of the image or by making himself aware that the seller overstated the condition of the car by choosing a non-representative image. By contrast, response-focused ER aims at altering and controlling the experiential, behavioral, and psychophysiological response when the emotion has already unfolded. The major representative for a response-focused ER strategy is suppression. In the auctioned-off-car example, the image-stimulus could unfold in a positive imagination of already driving this car, which the user then tries to inhibit or suppress subsequently. While this is an example of how emotions may be generated and regulated when seeing an image that provides additional information, our study focuses specifically on the impact of images that are not directly related to the auction.

In our study, it is reasonable to assume that ER capabilities have a moderating influence on the bidders' disposition to affective images. While both ER strategies outlined above were found to be effective in regulating positive emotions, previous research indicated that suppression can perform poorly in its effectiveness to mitigate negatively arousing emotions (Gross, 1998a). While this is considered the "emotional side," suppression is also presumed to have an "unemotional side." Suppression demands more cognitive load than reappraisal, since the emotion interference occurs at a later stage of the emotion generative process and therefore requires constant self-corrective action and self-monitoring (Gross, 2002; Heilman et al., 2010). Hence, reappraisal is often considered as the preferable ER strategy associated with better physical health, well-being, and even trading-skills (Fenton-O'Creevy et al., 2012; Gross and John, 2003).

4.2.5. Emotion Regulation and Decision Making

When it comes to behavior, only few studies so far have directly compared the effects of reappraisal and suppression on decision making. In previous studies—contrary to the belief that decision makers should suppress or at best, avoid strong emotions in order to take "unbiased" decisions (Seo and Barrett, 2007)—suppression was found to fail at mitigating effects of negative affective responses (Gross, 2002; Heilman et al., 2010). Reappraisal, by contrast, was associated with successful mitigation of stimuli and enhanced decision performance (Heilman et al., 2010) [33]. Reappraisal was found to both increase and decrease risk aversion in decision making, depending on the decision context (Heilman et al., 2010; Martin and Delgado, 2011; Sokol-Hessner et al., 2008). With respect to behavior, the results are therefore not fully conclusive and context depending.

In recent years, the impact of ER has been investigated in a number of psychophysiological studies, mostly using images or short films (e.g. Gross, 1998a; Urry, 2009). This research provided insight into the coherence of neural structures and ER. It was shown that reappraisal either does not influence or even decreases sympathetic activation, resulting in average or weaker affective responses (Gross, 1998a, 2002). Therefore, we do not expect a systematic effect on psychophysiological responses with respect to reappraisal. To the contrary, emotion suppression—even though as defined as the inhibiting expressive reactions—was shown to increase sympathetic activation in response to emotive stimuli, resulting in stronger affective responses (Gross, 1998a, 2002). For instance, previous research found that subjects who apply suppression strategies are physiologically more susceptible to watching visual stimuli than other subjects (Gross, 1998a). Correspondingly, we hypothesize that subjects with a comparatively high level of using suppression exhibit stronger SCRs:

> **Hypothesis 3d:** *The use of suppression strategies is positively correlated with the SCR amplitudes in response to seeing affective images.*

This influence has frequently been explained in the sense that the process of suppressing emotions is (cognitively) more demanding (Gross, 1998a, 2002). Following these insights, we hypothesize that displaying affective images does not only trigger more pronounced psychophysiological responses in suppressors, but that this is also reflected in their bids. This translates into our fifth research hypothesis.

> **Hypothesis 3e:** *The effect of competitive and community images on bids is moderated by the use of suppression strategies.*

The research hypotheses of our study are summarized in the research model depicted in Figure 4.1.

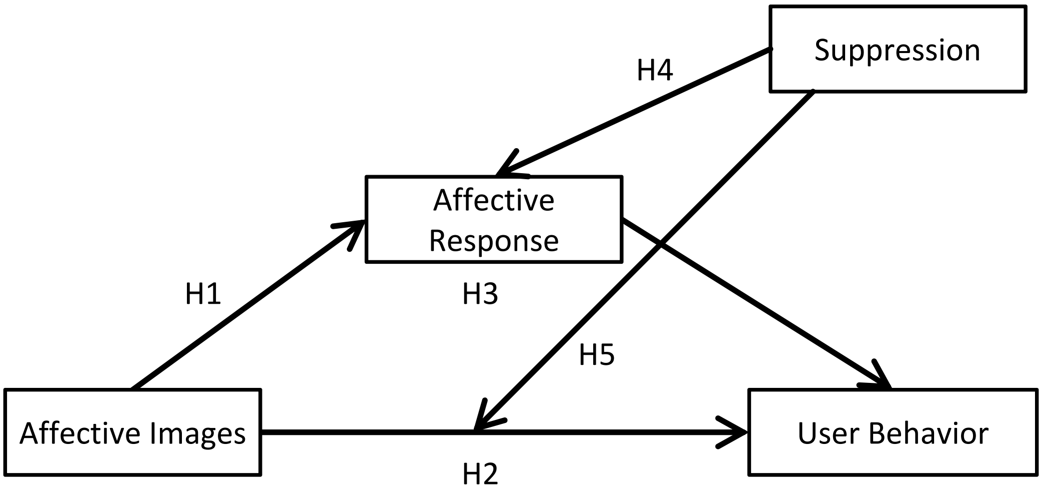


Figure 4.1.: Research Model.

4.3. Design and Method

In order to investigate the impact of (incidental) community and competition images on emotions and bidding behavior, we conduct a controlled laboratory experiment with psychophysiological measurements. In the experiment, each subject participates in 15 auctions and thereby accumulates so-called MU, which are later individually paid out in cash. Thus, in line with the induced value theory (Smith, 1976), decision making in this experiment is directly related to real monetary payoffs. In this experiment, 1 MU is equivalent to €0.04.

4.3.1. Treatment Structure

Our experiment constitutes a between-subjects design with three treatments. In the competition treatment (CMP), the bidders are shown images of sports events (e.g., runners passing the finishing line, boxers hitting each other, tumult on a rugby field) before the bid mask appears.[3] By contrast, in the community treatment (COM), the bidders are shown images that illustrate cozy family scenes (e.g., grandmother and grandchildren laughing, children playing with each other, father with his daughter on the beach).[4]

[3]In particular for CMP the images #1505, #5623, #8118, #8001, #8050, #8060, #8230, #8065, #8116, #8467, #8232,#8130, #8117, #8220 and #8231 of the IAPS database were used.
[4]In particular for COM the images #2341, #2345, #2598, #2080, #2091, #2154, #2156, #2158, #2216, #2274, #2303, #2332, #2340, #5830 and #5831 of the IAPS database were used.

The images were retrieved from the IAPS repository (Lang, 1995), in which all images are annotated with arousal and valence levels based on a large data sample. In our experiment, the images were selected to have comparable levels of arousal across the two treatments COM and CMP (M = 4.695 vs. M = 5.330). With respect to valence, COM images are inherently perceived as more pleasant in comparison to CMP images (M = 7.559 vs. M = 5.666). In the third, control treatment (NO), the bidders are shown no images at all. Instead of the images, a black screen is presented to the bidders in this treatment.

To assure that the single emotional cues resulting from the images are not distorted by the integral arousal induced by the dynamic market environment, we control for the emotional factors that might interfere:

- The auction result is not revealed at the end of a single auction round, but only at the very end of all auctions. This ensures the elimination of immediate emotions, such as joy of winning or frustration of losing (cf. Astor et al., 2013; Goeree and Offerman, 2003) which might also influence bidding behavior. This also restricts the set of possible auction formats to static (sealed-bid) auctions, since the Dutch or the English auction cannot be conducted without announcing the winner instantly, which again might trigger integral emotions (Bosman and Riedl, 2004).

- The current profit is not displayed to the bidders and hence potential cash-balance effects are mitigated. These design decisions also control for potential learning effects or belief updates that might otherwise occur during the course of auctions. In order to exclude final stage effects, subjects do not know exactly in how many auctions they will actually participate in. They were informed that the main part of the experiment would last about 45 minutes.

- To further assure a high level of control, subjects compete with computerized agents. This eliminates further auction dynamics such as rivalry. Also, subjects know that the computers follow an earlier determined bidding strategy which is not influenced by the human participants' bidding decisions. This design decision restricts subjects' anticipation of how their opponents might be affected in the respective treatment sessions.

4.3.2. Auction Process

In order to concentrate on the impact of incidental emotions on bidding behavior, we mitigate the level of integral arousal induced by the auction and deliberately choose a static (sealed-bid) auction format without interpersonal interaction. More specifically, each bidder participates in 15 FPSB auctions with 2 computerized opponents and independent private values (IPV). In an IPV auction each bidder knows his or her value for the good with certainty. In case the bidder placed the highest bid on the auctioned off good, the bidder wins the auction and earns his or her value minus the placed bid. Otherwise the profit is zero.

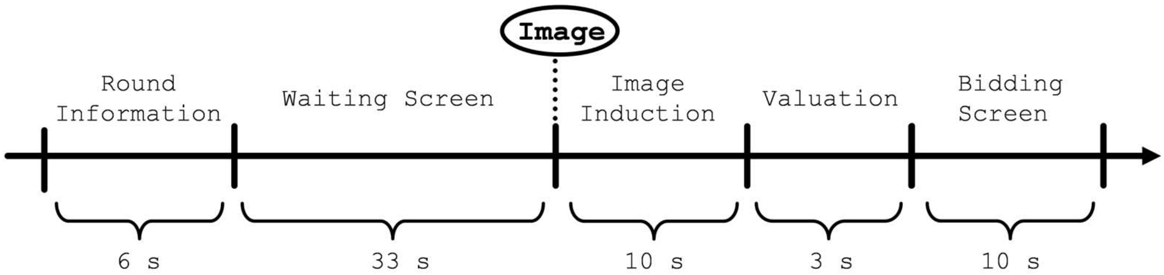


Figure 4.2.: Auction Process with Image Being Displayed at Event 'Image'.

The auction process of a single auction is illustrated in Figure 4.2. At the beginning of each auction, the bidder is informed about the round number. Then, a black waiting screen follows for 33 seconds. After that, depending on the treatment condition, a community image, a competition image, or a black screen is displayed for 10 seconds to the bidder. Then, the bidder is informed about his or her value for the commodity in this auction. Three seconds later the bidding screen appears. Now, the bidder has up to 10 seconds to place a bid. This ensures that the bids are made shortly after the bidder has seen the images. The bids are restricted to integers from 1 to 80, indicated by 80 buttons on the screen. Each button also contains a small bar which indicates the winning probability related to the bid. As subjects get no result information after each auction round and the bar assures that the bidder gets an intuitive sense of how risky his or her bid actually is (see Engelbrecht-Wiggans and Katok (2008) for a similar approach). After the bidder placed a bid, the next auction starts with the display of the round information. Finally, after all 15 auctions ended, each bidder is individually informed about his or her cumulated final profits.

Each subject received 3 times private values drawn from the set {60, 65, 70, 75, 80} MU in random order. In line with the extant experimental literature (e.g. Cox et al., 1988; Astor et al., 2013; Engelbrecht-Wiggans and Katok, 2008), this set of private values was chosen in order to avoid extreme values close to the lower or upper bound, would only increase the dispersion of bids. The computerized agents bid according to risk-neutral Nash equilibrium strategy and their value is drawn from a uniform distribution [0,100]. The subjects are told that the computerized agents place bids that maximize their expected profit if they participate against two identically programmed agents (see Astor et al. (2013); Engelbrecht-Wiggans and Katok (2008) for a similar procedure). In an auction with three risk neutral bidders the equilibrium bidding strategy $b(v_i)^*$ for bidder i with value v_i and is given by: $b(v_i)^* = 2/3v_i$ (Vickrey, 1961).

4.3.3. Procedure

The experiment was conducted at the KIT, and in accordance with the university's ethics guidelines. At the beginning of each session, the instructions were read to the participants, providing them with general information and details about the auction mechanism used. In order to ensure that the participants understood the procedure, they then had to successfully complete an online questionnaire consisting of 8 questions. After the experiment was over, subjects were asked to complete additional questionnaires. One complete experimental session took about one hour. In total 108 subjects participated in the experiment (mean age=22.80; 75 male; 33 female).[5] The participants were recruited from a pool of students using the ORSEE software environment (Greiner, 2004). Almost all subjects were of central European origin. The experiment consisted of 18 sessions with six participants each. Subjects received a show-up fee of € 4 and earned on average € 19.94. The z-Tree software environment was used to implement the experiment (Fischbacher, 2007). Each session started with an initial five minute rest period, which is needed for a proper calibration of the psychophysiological signals. The average room temperature in the laboratory was 25.1°C (77.2°F), which is within the methodological recommendations of the Society for Psychophysiological Research (Fowles et al., 1981). Seven subjects had to be excluded from the analysis because no adequate physi-

[5]We identified four economic outliers in the overall sample. A closer look reveals that those subjects also had comprehension problems, risk preferences that did not at all comply with their bidding behavior or, for example, did not even manage to place a bid within the time limit. These outliers were removed from the dataset.

ological measures could be assessed, resulting from measurement appliances that failed to operate (two subjects) or subjects being non-responders (five subjects). Additionally, we had to exclude seven single responses to the image induction, since due to motion artifacts the electrocardiogram signal could not be properly assessed. These problems are common when assessing physiological parameters. Also for the more fine-grained subsequent regression analysis two cases in which subjects did not manage to place a bid within the time limit were excluded. The reported results on bidding behavior are invariably robust against inclusion or exclusion of the above subjects or cases (cf. Table B.6).

4.3.4. Measures

Next to the subjects' bids, measured in MU, there are a number of further measures used in this study. Questionnaires were used at the end of the experiment in order to assess participants' perceptions during the auction phase and during the image induction phase. Therein, bidders were first asked to assess their individual emotional state during the auctions by means of the Affect Grid (Russell et al., 1989), that is, a two dimensional 9x9 matrix (pleasure-displeasure and arousal-sleepiness). Second, subjects were asked whether they thought that the images influenced their bidding behavior on a 7-point interval scale (1=not at all, 7=very much). Third, demographic factors such as age and sex were assessed. Fourth, in order to identify subjects' individually applied ER strategies, the ER questionnaire (ERQ) by Gross and John (2003) was used. The ERQ can be completed within five to ten minutes and consists of ten questions (6 for reappraisal and 4 for suppression). Each question is encoded on a 7-point interval scale. It is characterized by high reliability, high discriminate validity, and only little correlation with the dimensions of other commonly used personality questionnaires (Scheibe, 2011). Finally, we used the risk aversion questionnaire by Holt and Laury (2002) to assess subjects' individual risk preference. In this questionnaire, subjects have to make 10 choices between two lotteries with different levels of risk and expected payoffs. Based on the number of safe choices a subject chooses, the experimenter can approximate the subject's individual risk attitude.

With respect to psychophysiology, we focus specifically on phasic changes in SC and HR in response to seeing the affective images. In the analysis, we compute the amplitudes of SCRs (SCR.amp) as a measure for the intensity of immediate sympathetic reactions

(Dawson et al., 2011). Data treatment with respect to SCR.amp was done analogously to Section 2.3.4. Additionally, in order to reduce the between-subjects variability in the, data was normalized according to Section 3.3.4 in the subsequent regression analysis (i.e. all SCR.amp values were referenced to a subjects' average response to the value information).

Moreover, we investigate deceleratory responses in HR as a measure of parasympathetic activity. This allows for an evaluation of the perceived valence of external stimuli in response to images (Bradley et al., 2008; Ravaja et al., 2006) and other events such as winning an auction or a lottery, as described in the previous section. More specifically, external stimuli with a negative valence usually elicit stronger deceleratory HR responses than stimuli with a positive valence. The assessment was done identically as described in Section 3.3.4. Evidently, some participants did not react instantly to the image induction, as they concentrated their attention only after a view seconds to the displayed images. Prior research has especially focused on the cardiac phasic response upon 6 seconds past the visual stimulus (Lang et al., 1993). Analogously, we focus on the electrocardiogram signal within that particular time frame. In particular, we assess the magnitude of the deceleratory HR response by identifying first the maximum HR that occurred within the first 4 seconds after the stimulus, and subsequently the minimum HR that occurred up to 2.5 to 6 seconds after the stimulus. The deceleratory HR response is then calculated as the difference between the identified maximum and minimum HR within the relevant time frame. This parameter is a proxy for the valence dimension of emotions induced by the images (see Palomba et al. (1997) for a similar approach), and will be denoted by ΔHR in the following.

4.4. Results

4.4.1. The Influence of Images on Affective Processes in Electronic Auctions

In our research model we hypothesized that affective images can trigger emotions in the users, even though the images are unrelated to the task and displayed in the context of electronic auctions where there is real money at stake for the bidders.

As discussed above, emotions can be categorized in two dimensions: arousal and valence. Thereby arousal can be assessed through SCR.amp and valence through ΔHR. Before we can test our first research hypothesis (H3a), which relates to ΔHR only, we must first provide evidence that the induction of emotions in the treatment conditions (COM and CMP) was successful in the sense that it has resulted in significantly stronger emotions than in the control treatment (NO) in which no images were shown. To this end, we first compare SCR.amp between the treatment conditions and the control treatment condition. Figure 4.3 depicts the bidders' average change in Skin Conductance Level (ΔSCL) up to six seconds after the image induction and SCR.amp, indicating that the community and competition images in fact induce emotions of significant intensity in comparison to the control treatment where no images were shown. An ANOVA confirms that the treatment condition had a significant influence on the SCR.amp ($F(2, 96) = 4.768$, $p = .011$). Moreover, a post-hoc Tukey HSD test shows that the differences in SCR.amp between NO and COM (.069 vs. .117, $SE = .019$, $p = .030$), and NO and CMP (.068 vs. .120, $SE = .019$, $p = .020$) are significant, respectively. By contrast, the SCR.amp values in COM and CMP are comparable (.117 vs. .120, $SE = .019$, $p = .986$), which is in line with previous studies (Codispoti et al., 2001).

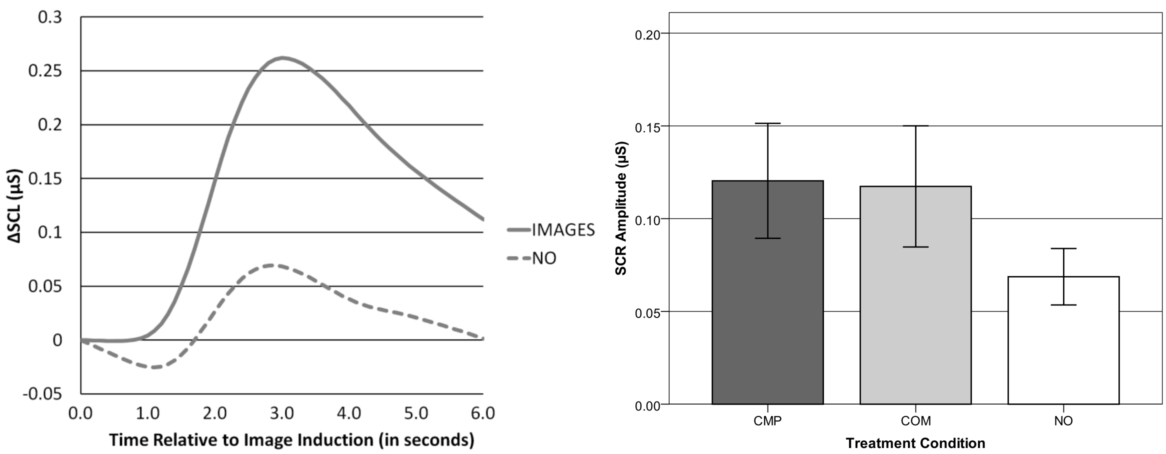


Figure 4.3.: Skin Conductance Level (SCL) and SCR.amp in Microsiemens (μS) to the Images Display versus a simple Flare Up on the Screen. (Error Bars: 95 Per Cent Confidence Intervals).

Having confirmed that the images induced an emotion of significant intensity, we can now examine the potential difference in subjects' experienced valence in response to the two image conditions.[6] Figure 4.4 depicts the mean HR drop relative to image display (ΔHR) for the COM and the CMP treatment. In line with H3a, subjects' cardiac deceleration is more pronounced in the CMP treatment than in the COM treatment. A t-test confirms that the difference in ΔHR between the CMP and the COM treatment is significant (3.572 vs. 2.680, $t(62) = 2.124$, $p = .038$). This is also confirmed by the results of regression I in Table 4.1 ($b = .205$, $SE = .100$, $t = 2.050$, $p = .045$).[7] Note that the regressions in Table 4.1 control for several additional factors, such as each subject's individual risk preference (safe_choices) and sex (dummy_female) as well as learning effects (auction_round) and the implied private value in a specific auction. Taken together, the analysis of the HR data provides support for our research hypothesis H3a. We can conclude that the community and competition images not only induced emotions of significant intensity in the bidders, but that these images also differ significantly in the valence dimension.

4.4.2. The Influence of Images on Bidding Behavior

Next, we focus on the impact of competition and community images on bids. Figure 4.5 shows the bidders' average bids for the three different treatments. In line with previous research, the bidders persistently place higher bids than the RNNE ($b^* = 46.66$) (Engelbrecht-Wiggans and Katok, 2008; Kagel and Roth, 1995).

In a first step, an ANOVA reveals that the treatment manipulation had a significant impact on the bids ($F(2, 101) = 4.069$, $p = .020$). Moreover, and in line with our research hypothesis H3b, a post-hoc Tukey HSD test shows that the bids in the COM treatment are significantly higher than the bids in the CMP treatment (54.537 vs. 51.730, $SE = 1.026$, $p = .020$). On average, the bids in the COM treatment are 2.703 MU higher than those in the CMP treatment. This difference is remarkable considering that the only difference between the treatments was that images with different social connotations were shown prior to the auction. As expected, average bids in the benchmark treatment (NO) are in between the two treatment conditions. However, the differences between

[6]Note that subjects' ΔHR cannot be properly assessed in the NO treatment, as there was no affective stimulus.

[7]The regressions summarized in Table 4.1 account for the fact of repeated measures for each subjects by using robust standard errors clustered by subject. Since only the participants in the COM and CMP treatments were exposed to affective images, the regressions in Table 4.1 are only based on those subjects who participated in either the COM or the CMP treatments.

Table 4.1.: Regression Tables For Bids. Note: The Regressions are Based on Robust Standard Errors Clustered by 64 Subjects. Measures for ΔHR and SCR.amp are transformed according to $ln(x+1)$.

	Dependent variables															
	Δ HR				Bid				Bid				SCR.amp			
Independent variables	**B**	**SE**	***t*-Stat**	***p*-value**	**B**	**SE**	***t*-Stat**	***p*-value**	**B**	**SE**	***t*-Stat**	***p*-value**	**B**	**SE**	***t*-Stat**	***p*-value**
value	.000	.000	-1.350	.181	.539	.036	15.080	<.001***	.539	.036	15.050	<.001***	-.003	.002	-1.570	.121
dummy_competition (CMP)	.205	.100	2.050	.045*	-2.809	1.034	-2.720	.008**	-2.597	1.067	-2.430	.018*	.012	.053	.230	.820
suppression					1.322	.528	2.500	.015*	1.281	.538	2.380	.020*	.048	.027	1.830	.072^{+}
CMP x suppression					-2.403	.864	-2.780	.007**	-2.423	.873	-2.780	.007**	.010	.056	.180	.857
reappraisal	.013	.058	.220	.828	.655	.393	1.670	.101	.666	.402	1.660	.103	-.112	.041	-2.720	.009**
CMP x reappraisal	-.007	.093	-.070	.944	.306	.847	.360	.719	.290	.845	.340	.733	.119	.064	1.870	.066^{+}
safe_choices	.024	.026	.910	.367	.761	.292	2.610	.011*	.786	.285	2.750	.008**	-.002	.020	-.120	.902
dummy_gender_female	.239	.099	2.400	.019*	.501	1.425	.350	.726	.704	1.400	.500	.617	-.024	.061	-.390	.697
auction_round	.000	.000	-.170	.864	.026	.065	.390	.696	.026	.065	.390	.697	-.027	.004	-7.100	<.001***
Δ HR									-1.006	1.133	-.890	.378				
constant	1.026	.149	6.866	<.001***	12.510	3.124	4.003	<.001***	13.550	3.424	4.076	<.001***	.900	.171	5.246	<.001***
	$n = 951$				$n = 951$				$n = 951$				$n = 951$			
	$R^2 = .163$				$R^2 = .349$				$R^2 = .352$				$R^2 = .096$			

$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

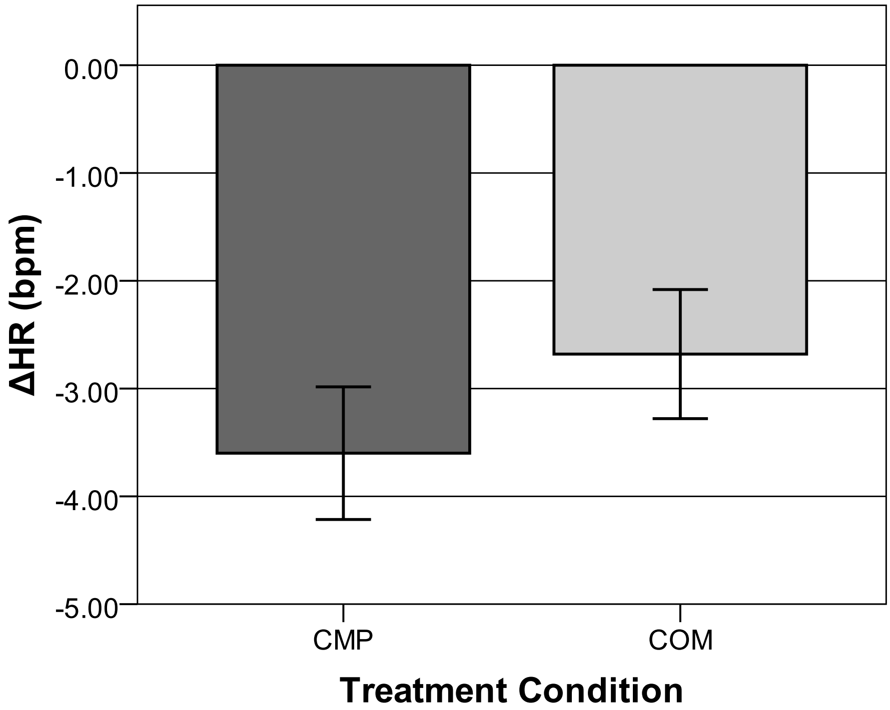


Figure 4.4.: HR Drop (ΔHR) in beats per minute (bpm) subsequent to the image induction between CMP and COM. (Error bars: 95 Per Cent Confidence Intervals).

NO and COM (53.814 vs. 54.537, $SE = 1.040$, $p = .767$), and NO and CMP (53.814 vs. 51.730, $SE = 1.026$, $p = .110$) are not statistically significant, respectively. Regression II in Table 4.1 provides further evidence that there is a significant difference in bids between the COM and the CMP treatments ($B = -2.809$, $SE = 1.034$, $t = -2.720$, $p = .008$). Expectedly, subjects' value and risk attitude (i.e., the number of safe choices) enter the regression with high significance for all models with bid as dependent variable. Higher values and higher risk aversion increases average bids. This is in line with previous research on FPSB auctions (cf. Kagel and Roth, 1995). We cannot observe a significant impact of a bidder's sex on bids.

Interestingly, subjects reported that they did not think that the images had an influence on their bidding behavior ($M = 2.290$, $SD = 1.287$). Regarding their emotional state (on the Affect Grid), subjects reported on average a valence score of $M = 6.114$ ($SD = 1.602$) and an arousal score of $M = 3.300$ ($SD = 1.680$), indicating that they were in a positive and relaxed mood during the image induction. A set of ANOVAs

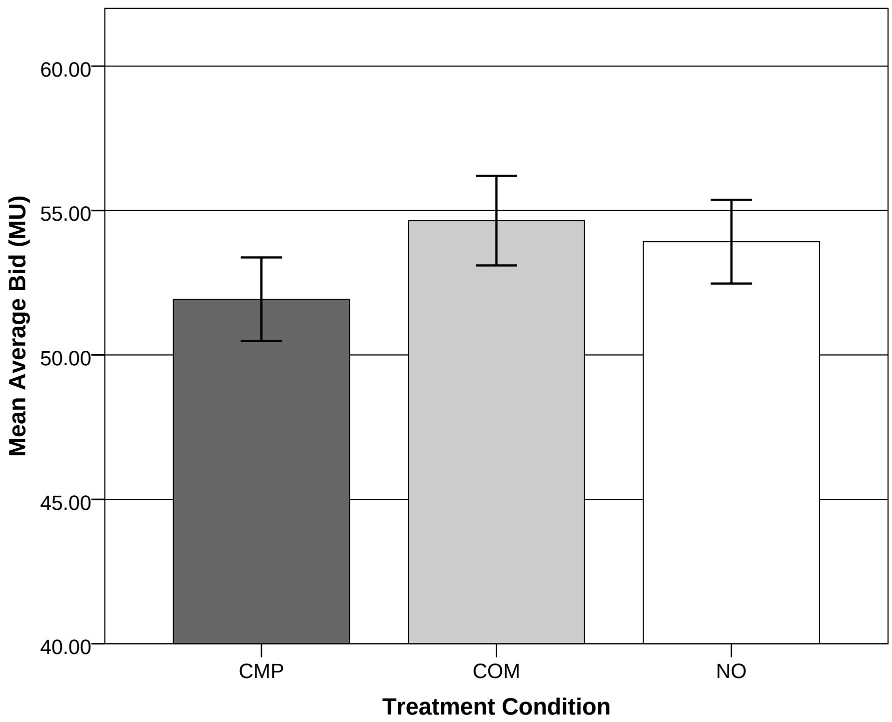


Figure 4.5.: Subjects' mean average bids in the different treatments. (Error bars: 95 Per Cent Confidence Intervals)

reveals that there are no significant differences in perception between the three treatments on subjects' self-perceived valence ($F(2, 101) = .335$, $p = .716$) and arousal ($F(2, 101) = .765$, $p = .468$). In other words, the images evidently did not alter the conscious emotional state significantly, while the psychophysiological data provides evidence that the images in fact had an influence on the bidders' affective processes. Therefore, it seems plausible that the effect of the affective images on bidding behavior is unconscious in nature. Taken together, we can reject the null hypotheses in favor of our research hypothesis H3b. The bidders exposed to competition images place lower bids than bidders exposed to community images.

4.4.3. Mediation Analysis

Next, we examine H3c, i.e., to what extent subjects' bids are mediated by their affective processes, as measured by ΔHR. In our research model in Figure 4.1, this indirect effect is captured by the conjoint path of Affective Images through Affective Response to User Behavior.

We test H3c by employing a mediation analysis (cf. Preacher et al., 2007). Regressions I to III in Table 4.1 provide the results of the corresponding regression analysis on the mediator (Regression I), and on the bids. The latter regressions either do not take ΔHR as covariate into account (Regression II) in order to determine the total effect, or include ΔHR as covariate (Regression III) in order to determine the size of the direct and indirect effect. According to the suggestion of Hayes, we evaluate the significance of the indirect effect in a bootstrapping procedure based on 5,000 samples (Hayes, 2009). We find a significant total effect ($TE = -2.809$, $SE = 1.034$, $LL = -4.875$, $UL = -.743$), as well as a significant direct effect ($DE = -2.597$, $SE = 1.034$, $LL = -4.729$, $UL = -.464$), and a significant indirect effect ($IE = -.207$, $SE = .115$, $LL = -.465$, $UL = -.008$)[8] where LL and UL refer to the upper and lower limits of the 95 per cent confidence interval. In summary, we can conclude that, in line with our research hypothesis H3c, a bidder's affective processes, as measured here by ΔHR, partially mediate the impact of images on bids. We will return to the implications and limitations of this result in the discussion.

4.4.4. The Moderating Influence of Suppression

Finally, we examine the moderating influence of suppression. The scores for suppression and reappraisal were obtained by computing the means of both item scales. In our research model, we hypothesized that applying suppression increases the users' psychophysiological response to seeing affective images (H3d) as well as their impact on bidding behavior (H3e).

In line with our research hypothesis H3d and with previous results from the literature, regression IV in Table 4.1 indicates that subjects who apply suppression strategies exhibit stronger SCR.amp ($B = .048$, $SE = .027$, $t = 1.830$, $p = .072$). However, this effect is only marginally significant and we thus find only weak support for H3d. On the other hand, we find that reappraisal significantly decreases average SCR.amp in the COM treatment ($B = -.112$, $SE = .041$, $t = -2.720$, $p = .009$), while this effect is mitigated in the CMP treatment ($B = .119$, $SE = .064$, $t = 1.870$, $p = .066$).

[8] The indirect effect (IE) can be calculated by multiplying its constituent paths. In this case $IE = -.205 = -1.006 * .206$ (discrepancy is due to rounding errors).

This provides evidence that—depending on the context—reappraisal can be reflected in smaller SCR.amps. We will return to this result in the discussion. Finally, we find that SCR.amps mitigate over the sequence of the 15 auction rounds.

Next, we examine whether the use of suppression amplifies or mitigates users' affectedness to affective images in electronic auctions. In order to control for this moderating influence (cf. H3e), we included the corresponding interaction term in the regressions of the mediation (CMP x suppression). For completeness, we also controlled for a moderating influence of reappraisal (CMP x reappraisal) in these regressions. As can be seen in regression III in Table 4.1, the direct effect of affective images on bids is conditional on the extent to which a subject applies suppression. Figure 4.6 provides a graphical illustration of this relationship.

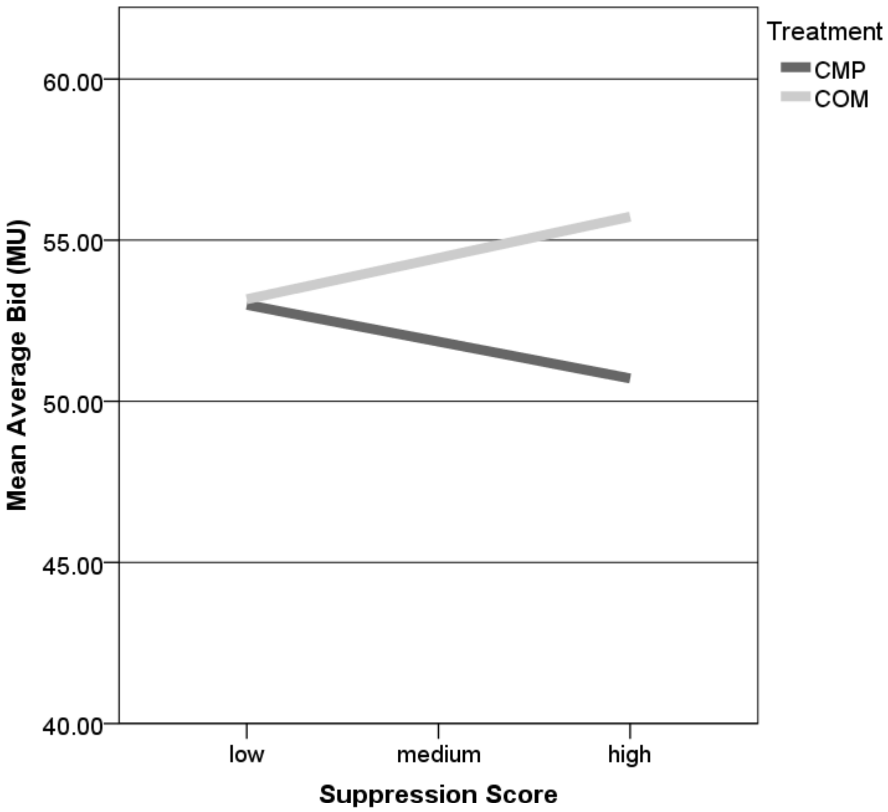


Figure 4.6.: Illustration of the moderating influence of suppression.

In the COM treatment, using suppression strategies has a significant positive influence on bids (b = 1.322, SE = .528, t = 2.500, p = .015). Moreover, the interaction term CMP x suppression reveals that the influence of suppression on bids is reversed in the

Table 4.2.: Conditional direct effect of treatment on bids at values of suppression. Note: The regressions are based on robust standard errors clustered by subject.

	Dependent Variable Bid						
Suppression Score	**B**	**SE**	***t*-Stat**	***p*-value**	**Sig.**	**LLCI**	**ULCI**
-1.000	-.174	1.429	-.121	.904		-3.029	2.682
.000	-2.597	1.067	-2.433	.018	*	-4.729	-.464
1.000	-5.020	1.327	-3.784	<.001	***	-7.671	-2.369

* $p < .05$, ** $p < .01$, *** $p < .001$

CMP treatment ($b = -2.403$, $SE = .864$, $t = -2.780$, $p = .007$), i.e., there is a significant negative influence of suppression on bids. The corresponding moderation analysis provides further evidence for a conditional direct effect of affective images on bids (see Table 4.2). Subjects with a low score of suppression seem to be unaffected by the affective images ($ME = -.174$, $p = .904$), while subjects with a medium ($ME = -2.597$, $p = .018$) or high ($ME = -5.020$, $p < .001$) suppression score are affected significantly. In summary, we can therefore reject the null hypothesis in favor of our research hypothesis H3e. The effect of competitive and community images on bids is moderated by the use of suppression. The main results of this study are summarized in Figure 4.7.

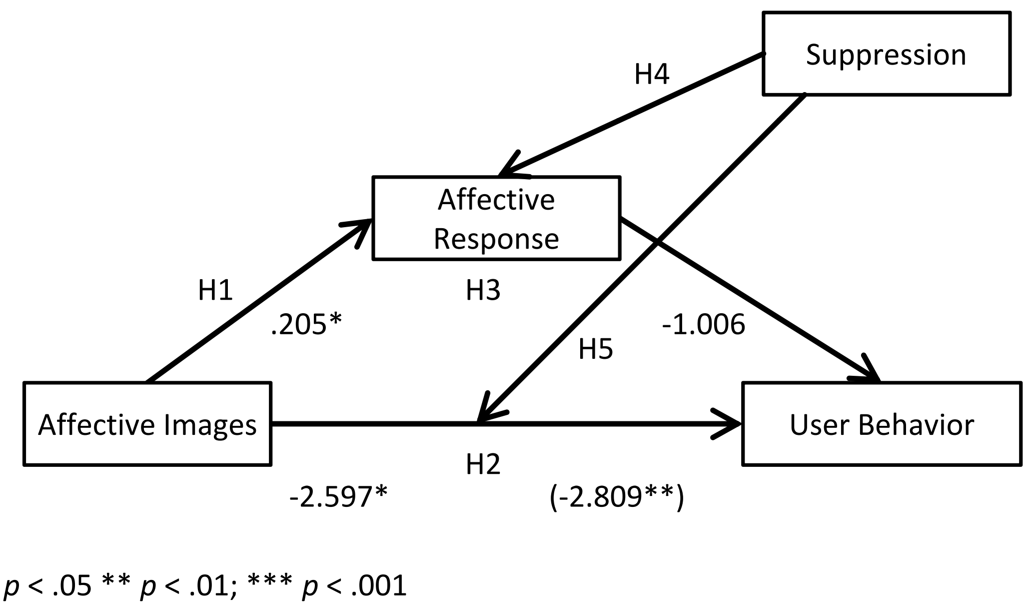


Figure 4.7.: Results of mediation analysis using unstandardized coefficients.

4.5. Discussion and Conclusions

4.5.1. Managerial Implications

From the perspective of Internet auction platforms, our study shows that even seemingly unrelated design elements can cause affective processes in the users which eventually influence their behavior. Images are widely used in platform design of electronic markets. In particular, platforms seem to either use community images, which are meant to induce a sense of social intimacy and warmth, or competition images, which are meant to induce a competitive spirit in the bidders. Our study shows that bidders place higher bids when community images are displayed than when competition images are displayed. Evidently, the designers of such electronic market platforms need to be aware of how such images impact market outcome. Our results suggest that in order to maximize revenues, the user interface should rather induce a sense of social warmth than a sense of competition. In reverse, this questions the marketing strategy of the market leader ebay.com, for example, which suggested to its customers in advertisement campaigns as well as through images on its website that "it's better when you win it."

Our results also show that the designers of electronic markets should be well aware of the ER strategies employed by their users. In our study, those users who employ suppression are found to bid significantly higher in the presence of community images, but also significantly less in the presence of competition images. Taken as a whole, users who apply suppression are more affected in their behavior. Auctions inherently pick those bidders as winners who have a systematic tendency to place higher bids than the other bidders (Lee and Malmendier, 2011). Profit-maximizing sellers should thus account for individual behavioral aspects of their consumers, e.g., the influence of interpersonal differences in ER. Consequently, it is important for marketers to identify the ER strategy of their users (e.g., through a questionnaire during registration) in order to individually adapt the interface for each user accordingly. In addition to maximizing profit in single auctions, adjusting the interface according to the ER strategies of the users may also improve user experience and thus the success of the platform in the long run. For instance, our results show that the behavior of bidders with a low suppression score, but a high reappraisal score is unaffected by the images. However, these bidders experience weaker emotions in response to community images than in response to competition images (see moderating influence of reappraisal on SCR.amp).

Finally, from the perspective of market participants, it is important to highlight that—subject to interpersonal differences in ER—affective images can have an impact on their behavior. However, applying suppression is not disadvantageous per se. While the bidders place higher bids in response to seeing community images, their bids are lower and thus their profits higher when seeing competition images. Furthermore, the use of psychophysiological measurements during market participation may also be to the benefit of customers. In this context, Menon and Kahn (2002, p.39) concluded: "rather than designing static websites, a retailer could design a website to interact with the consumer and adjust to his or her emotional state". Building on psychophysiological measurements, providing users with biofeedback could ultimately protect market participants and the organizations they represent from taking disadvantageous decisions (Cyr, 2008). Customers might find biofeedback helpful for detecting a state of poor ER, which may then be utilized to turn a previously unconscious influence of affective processes on economic behavior into a conscious, deliberate choice.

4.5.2. Theoretical Implications

Previous studies focused particularly on the impact of using facial features in product images (Cyr et al., 2009; Hassanein and Head, 2006). As a product image is an important medium for forming attitudes and expectations about the product for sale, it can be regarded as a stimulus that triggers an integral emotion. By contrast, our study focused on images which are unrelated to the task and we can show that also incidental emotions can have an impact on economic decision making in electronic markets. This insight bears implications for the design of "exciting" marketplaces, as excitement that is derived outside actual market participation, e.g., through graphic and acoustic elements on the website such as videos, sounds and images, can have a systematic influence on market outcome. Changes in the bidders' emotional states, whether derived from participation in an electronic market (auction) or induced by an outside event, are thus relevant for the market outcome. It would be interesting to investigate the influence of further sources of incidental emotions on the behavior of market participants. In this context, Riedl (2013) provided a comprehensive literature review on how interacting with information systems per se can induce considerable levels of arousal and "technostress." For instance, experiencing a system breakdown can induce high levels of the stress hormone cortisol in the users (Riedl et al., 2012). Such incidental affective processes might in turn increase or decrease the users' willingness to take risk in electronic markets. Interestingly, by combining self-report data with psychophysiological measurements we can conclude that the influence of incidental emotions on behavior is unconscious. In the questionnaire, participants indicated that they were not affected by the images shown, neither emotionally nor economically. By taking into account the psychophysiological data, however, we found a mediating relationship of bidders' affective processes on bids. This highlights how research on psychophysiology can provide additional insights that complement more traditional research approaches, such as psychometric scales. Clearly, with the use of self-report measures alone, this relationship could not have been confirmed. It is important to highlight though that (i) taking into account the users' self-perception is important for assessing characteristics which are not reflected in psychophysiology, e.g., whether the effect is conscious or unconscious in nature, and (ii) that of course also psychophysiological measurements bear limitations (see next subsection).

Finally, our results indicate that ER strategies, particularly emotion suppression, can act as moderators of the impact of the emotional state on bidding behavior. Even though previous literature provided evidence that suppression has emotional and non-emotional costs, which are reflected in psychophysiology (Gross, 2002; Heilman et al., 2010), subsequent economic behavior in electronic auctions has not been considered under controlled laboratory conditions so far. Our results show that suppression not only struggles at mitigating the psychophysiological but also the behavioral response. Consequently, this insight suggests that the users' ER capabilities should be taken into account when investigating the impact of emotions on the behavior of market participants. For instance, the emotional bidding framework of Adam et al. (2011) neither accounts for the influence of incidental emotions nor for a moderating effect of ER.

4.5.3. Limitations and Future Research

Evidently, there are several limitations that exist in this study. First, as it is often the case with observational studies, it is difficult to disentangle causality from correlation. Therefore we cannot definitely answer whether suppression is the reason for subjects' strong reactions to the images shown or whether it is another trait that drives the pattern—which then would be correlated with suppression. For instance, we only found marginal evidence for our research hypothesis H3d (p = .072), i.e., that suppressors experience stronger emotions in response to seeing affective images. However, taking into account that our subjects belong to a relatively homogeneous group (i.e., all students with similar age) the interplay of the economic and psychophysiological results provides coherent results, such that suppression can be suspected to play a moderating role in users' behavior. In general, more IS research is needed to examine the role of ER on the users' affective processing and behavior. Although our findings are consistent with recent research results that poor regulation can be detrimental to trading performance (Fenton-O'Creevy et al., 2012), the relationship between ER and economic behavior deserves more attention. For instance, it might be interesting for future studies to actually manipulate subjects' usage of suppression strategies via certain tasks that stimulate suppression (Heilman et al., 2010). However, researchers should be aware that subjects who generally apply reappraisal techniques might struggle to use suppression and vice versa (Volokhov and Demaree, 2010).

Second, we considered a FPSB auction with computer opponents in order to attain a high level of control over the environmental conditions and to exclude alternative explanations for the observed effects. However, this may have limited the generalizability of our results as most electronic auction platforms, such as eBay, employ a dynamic auction mechanism. Moreover, contrary to our experimental design, bidders usually have some uncertainty about their private value of the good. However, these aspects are likely to rather increase bidders' emotionality during auction participation (Ariely and Simonson, 2003; Ku et al., 2005), which may also lead to more pronounced results.

Third, while HR and SC provide interesting insights into the affective processes of auction participants, it is important to highlight that these measures also bear limitations. The advantages are that psychophysiological measures can be assessed in the very moment of decision making without the necessity to interrupt users and cause distraction. On the other side, psychophysiological measures (i) have a high degree of variance and (ii) cannot assess the users' individual perceptions about the quality of the emotions (Dimoka et al., 2012; Riedl et al., 2010). For instance, with respect to the mediating role of affective processes, our analysis only reveals a partial mediation while the direct effect of affective images on bids might actually be fully mediated. Due to the high variance of psychophysiological data, it might be interesting for future research to compute multimodal arousal and valence parameters based on multiple parameters—including both psychophysiological as well as self-perception data. It should be highlighted that self-report measures will continue to be a valuable source of information, also or especially in the presence of complementary psychophysiological data. For example, without the use of self-report questionnaires it would not have been possible in our study to state whether the effect of images on behavior is conscious or unconscious.

In general, we believe that using tools from cognitive neuroscience and psychophysiology will be able to provide more insight into the unconscious processes shaping users' expectations, attitudes and behavior. More research is needed here to investigate how internal and external affective influences are processed and how these processes are shaped by personality traits and cultural background (Cyr, 2008; Zahedi and Bansal, 2011). For instance, how does technostress shape the users' beliefs and attitudes towards a platform? What other elements of the user interface can induce affective processes in market participants and change their behavior? To what extent do personality traits and cultural background moderate the users' conscious and unconscious affective processes? We believe that answering these questions can contribute to building better information systems.

4.5.4. Conclusions

In conclusion, affective images can have an influence on market participants' affective states and subsequently on their economic behavior—even when the images are unrelated to the task. Moreover, those bidders who try to suppress their emotions are even more strongly affected by them. While the self-report measures indicate that this process is unconscious in nature, the use of psychophysiological methods shows that bidders' affective processes partially mediate the relationship between the display of affective images and market behavior. Taken as a whole, the results of this chapter suggest that market design should carefully consider which images are displayed to the users and that the user interface should be individually adapted according to the users' ER capabilities. Furthermore, we conclude that combining self-report measures with psychophysiological measures is a promising approach for the evaluation of user interfaces (Vom Brocke et al., 2013), because the impact of affective processes on behavior can be unconscious. As unobtrusive biosignal technology is becoming available to a broader community, it seems promising for the users and designers of electronic markets and other IT artifacts to apply such measures even in the field (Nunamaker et al., 2011). Eventually the use of biosignals may help to better understand the coherence of incidental emotions and decision making and ultimately even support users in their goal to adequately respond to distracting emotional stimuli that could otherwise impair their behavior.

Chapter 5.

Enhancing Emotional Awareness and Rewarding Emotion Regulation

As known from literature, but also as indicated by the previous chapters, emotional processes can have material consequences on individuals' financial decision performance. Also traders and private investors are well aware of this circumstance. However, typical learning approaches for de-biasing fail to overcome emotionally driven financial dispositions; mostly because of subjects' unability for self-monitoring. The tool introduced in this chapter aims at improving users' decision making performance by (i) boosting their awareness to their emotional state and (ii) punishing skills of poor ER. To that end we design, implement and evaluate a serious game based NeuroIS tool that continuously displays the player's individual emotional state, via biofeedback, and adapts the difficulty of the decision environment to this emotional state. The design artifact is then evaluated in two laboratory experiments. Taken together, our study demonstrates how IS design science research can contribute to improving financial decision making by integrating tools from cognitive neuroscience in IT artifacts.

5.1. Introduction

Indeed, the human nervous system is fascinating. While in one moment it enables us to achieve high performances—independent whether in sports or in natural sciences—the next moment it allows us to calm down and enjoy the beauty of a quiet sunny afternoon. No matter if consciously or subconsciously, the human nervous system thereby continuously adjusts bodily functions in order to match the entire system to ongoing changes in environmental demands. Central in this process are emotions. Emotions facilitate our interactions with the socioeconomic environment; they foster meaningful interpersonal interactions, prepare behavioral responses, and enable us to take beneficial decisions (Gross, 2007). Unfortunately, however, emotions are sometimes inaccurately processed. Emotions can get “out of control” (Loewenstein, 1996). In the heat of the moment, human decision makers can be overwhelmed by their emotions and—under the influence of high levels of arousal—lose control over their actions. In business, such processes can have material consequences for the organizations the decision makers represent. As it turns out, there is a strong misbalance between emotions and their consequences. While the emotions are passing, the consequences of the actions which they caused are not; they can very well be long-lasting. This applies even more for important decisions, because “important decisions induce powerful emotions in decision makers” (Loewenstein, 2000, p. 429). To frame it differently, it is highly important for decision makers to correctly process emotions, because emotions particularly affect important decisions. Financial decisions fall into this category (Lucey and Dowling, 2005). There are, however, strong interpersonal differences in the capabilities of adequate emotional processing (Lo and Repin, 2002; Lo et al., 2005). There is evidence that traders’ and investors’ ER capabilities correlate with their skills in trading (Fenton-O’Creevy et al., 2011, 2012). This also means that decision makers with low ER capabilities are more likely to take maladaptive decisions, leading to undesired outcomes. Hence, improving the ER capabilities of decision makers might also be an important step for their organizations. One approach to boost this improvement process is to employ sophisticated IS tools that provide decision guidance and facilitate the skill development process.

In this chapter, it is our objective to help decision makers with improving their ER capabilities in the context of financial decision making. Therefore, a NeuroIS tool is designed, implemented, and evaluated (Vom Brocke et al., 2013). More precisely, we provide a dynamic learning environment which is based on a serious game with real-time biofeedback. In the game, the player is continuously confronted with financial decisions. The difficulty of these decisions is directly linked to his or her individual emotional state which is also indicated via biofeedback. Based on HR measurements, the game incorporates the player’s arousal level into the game task. The player wears an electrocardiogram sensor that transfers the data via Bluetooth to the game. Depending on the player’s ability to regulate his or her emotions, the financial decision scenario of the game adjusts in real-time and thereby becomes more (or less) difficult. The design artifact is thus also a use case for how information systems can incorporate tools from cognitive neuroscience.

This chapter is organized as follows. The conceptual foundations of our approach are outlined. We then introduce the concept of ER and summarize previous results regarding the impact of ER on financial decision making. Based on this theoretical background, requirements, design decisions, and implementation of our design artifact are presented. The design artifact is then evaluated in two laboratory experiments (Evaluation Study I and II). In the conclusion the implications of the approach and challenges for future research in the field of NeuroIS design science research are outlined.

5.2. Theoretical Background

5.2.1. Emotion and Cognition in Financial Decision Making

In classical economic theory the decision maker is typically described as "as a perfectly rational cognitive machine" (Sanfey et al., 2003, p. 1755). This assumption certainly has advantages in economists' strive to formalize and model human decision making; and then to squeeze it into the boundaries of expected utility theory. However, this "consequentialist perspective" (Loewenstein et al., 2001, p. 267) does not leave much room for the incorporation of emotions on cognition and decision making and therefore struggles with a broad body of literature which provides sufficient evidence that the assumption of a perfectly rational *homo economicus* does not hold for most human decision makers (Bechara and Damasio, 2005; Loewenstein et al., 2001; Shiv et al., 2005). From a purely economic standpoint, emotions were originally considered as a violation of expected utility theory and their influence as disturbing and even counterproductive for the quality of financial decision making (Bechara and Damasio, 2005). And with respect to financial decisions, emotions are suspected to be the underlying driving force for a whole group of biases, such as the disposition effect (Weber and Camerer, 1998), loss aversion (Novemsky and Kahnemann, 2005; Sokol-Hessner et al., 2008), and the phenomenon of auction fever (Adam et al., 2012; Ku et al., 2005). These biases have been shown in a broad range of field studies (Ku et al., 2005; Shefrin and Statman, 1985) and laboratory experiments (Novemsky and Kahnemann, 2005; Weber and Camerer, 1998). They can result in significant financial losses and therefore have highly adverse consequences for the decision makers.

Despite these biasing effects emotions can have, insights from economic psychology widened the picture in several aspects. The majority of psychologists meanwhile view decision making in a dual process framework, stating that depending on the context, humans process reality in two fundamentally different ways: the slow and analytical *rational system* and the fast and intuitive *experiential system* (Kahneman and Frederick, 2002). Especially in environments where fast processing is required, subjects tend to rely on their emotions and follow an so-called "affect heuristic" (Slovic et al., 2007). Essentially, the affect heuristic states that human decision makers integrate context specific affective feelings into perception and their decision making process. Somewhat related, Isen argued that "positive affect" can even be of positive influence for creative problem solving, cognitive processing and decision making under complex and stressful situations (Isen, 2001). Research from the field of cognitive neuroscience provided evidence that activation in distinct neural circuits, correlating with positive as well as negative affective states, can increase but also decrease the likelihood for certain financial mistakes (Kuhnen and Knutson, 2005; Peterson, 2007). In this regard, Kuhnen and Knutson concluded that "financial decision making may require a delicate balance" and that "excessive activation of one mechanism or the other may lead to mistakes" (Kuhnen and Knutson, 2005, p. 767).

Emotions' impact on financial decision making became evident in a multitude of studies (e.g. Adam et al., 2012; Loewenstein, 1996; Riedl et al., 2010). It is important to note, however, that most of these studies refer to contextualized situations and "the context can influence how we process stimuli that may have affective properties" (Rolls and Grabenhorst, 2008, p. 230). Put in different words, affective processes are highly context dependent and up to today it is not clear what in general the emotional triggers are that guide *optimal* financial decision making. A series of experiments specifically accounted for the interplay of emotions and information processing—and found that emotions in fact can contain relevant information (Bechara, 2004). In their somatic marker hypothesis, Bechara and Damasio concluded that emotions seem to be both a source of biases as well as an important mechanism for advantageous decision making (Bechara and Damasio, 2005). The authors showed that the experience of emotions itself is a mandatory prerequisite for advantageous decision making. More specifically, the authors found that those subjects with brain lesions, that are critical for the processing of emotions, performed worse in a card game under ambiguity than healthy subjects (Bechara and Damasio, 2005; Bechara et al., 1997). Bechara and Damasio concluded that so called "somatic markers"—in essence emotional responses to information events—can affirmatively guide our focus of attention. The somatic marker hypothesis therefore states that "decisions are aided by emotions, in the form of bodily states, that are elicited during the deliberation of future consequences and that mark different options for behavior as being advantageous or disadvantageous" (Naqvi et al., 2006, p. 260). Depending on the context, it was however also been shown that such emotional processes can also have disruptive effects (Adam and Kroll, 2012). It is hence important to note that emotions cannot always "be trusted as leading to good or bad decisions" (Shiv et al., 2005, p. 438). But it can be retained that a well-functioning recognition of these emotional bodily states is a necessary prerequisite for the decision whether it is better to follow an emotional response or to inhibit it. It can also be stated that the strict separation of emotions and cognition drawn in the past is rather outdated (Phelps, 2006).

While economic theory for a long time neglected the influence of emotions on financial decision making, professional trades and investors at banks are well aware that emotions can have significant influence on their decision performance. Therefore they are highly interested in eradicating such emotional dispositions (Fenton-O'Creevy et al., 2011). Fenton-O'Creevy and colleagues found in an interview based study with professional traders that major losses often resulted in periods of high risk aversion and overcautious behavior (Fenton-O'Creevy et al., 2011). Furthermore, a period of major gains could result in excessive self-confidence and risk prone behavior. Experimental findings point towards similar results (Novemsky and Kahnemann, 2005; Weber and Camerer, 1998). Traders and private investors have already understood that they cannot simply ignore their emotional states, and that certain decision making biases, such as for instance illusion of control (Fenton-O'Creevy et al., 2003), are even beyond conscious awareness.

Lo and Repin conducted a study with day-traders, which were connected to physiological measures (Lo and Repin, 2002). The authors found that traders do in fact have high states of arousal during the trading day, with strongest activation during periods of high market volatility. In a subsequent study, Lo and colleagues found that "extreme emotional responses are apparently counterproductive from the perspective of trading and performance" (Lo et al., 2005, p. 357). This provides further support for the notion that arousal can adversely affect rational cognition and decision making (Kuhnen and Knutson, 2005).

Weak impulse control strategies, high emotional reactivity and the exposure of high levels of arousal, which might threaten rational processing, are often associated with poor investment performance (Peterson, 2007). It has also been shown that trading success is correlated with certain personality traits. In particular, introversion, emotional stability, and openness to new experiences have been found to be associated with good trading performance (Peterson, 2007). Peterson found that it is important for traders to be aware of their own "fallibility" and to avoid to be overpowered by their emotions. The author recommended to "use awareness of your emotional state to generate a personal warning signal" (Peterson, 2007, p. 76). Similarly, Biasis and colleagues found that "self-monitoring enhances trading performance" (Biasis et al., 2005, p. 308). As these findings indicate, an increased awareness to one's own emotional state might help traders to identify a state fueled with high arousal, which could eventually threaten decision performance (Fenton-O'Creevy et al., 2012, 2011). In addition to the mere awareness of arousal, however, it is also important to develop strategies in order to "interpret and manage affective states" (Peterson, 2007, p. 75). In this context, Seo and Barret found that effective regulation of emotional states is positively correlated with trading performance in a trading simulation environment (Seo and Barrett, 2007).

5.2.2. Emotion Regulation

The concept of ER has gained wide attention in psychological research in recent years (Gross, 2007) and will be explained here in more detail. According to the concept of ER, emotions can determine and change the way how we perceive certain situations and thereby influence the way we react to them. Thus, emotions act as response tendencies: they suggest distinctive responses to a certain situation, which an individual may or may not follow (Gross, 1998b). In this sense, emotions "reflect the status of one's ongoing adjustment to constantly changing environmental demands" (Thayer and Lane, 2009, p. 85). The process model of Gross (Gross, 1998a) is widely known and acknowledged in the field of ER research. It stems from the assumption that emotions are generated in an emotion generative process. As we have already seen in the previous chapter, research distinguishes primarily between antecedent- and response-focused ER strategies.

Antecedent ER strategies apply while the emotion is still unfolding and has not reached its top. The most prominent representative is cognitive reappraisal. These strategies will be explained on the basis of a short example. Consider for instance, an impatient IT manager waiting for a developer to fix a potential security hazard in the system. Cognitive reappraisal could now manifest in becoming aware that the manager could usefully utilize the waiting time, for instance, by reassuring that recently a backup copy was made. Contrarily, response-focused ER aims at suppressing the experiential, behavioral, and physiological response when the emotion has already completely unfolded. The most prominent strategy for response-focused ER is suppression. In the IT manager example, suppression could enfold in the way that the manager gets really frustrated, but then decides to not express this experienced emotion in order to not alarm his colleagues. In fact, emotions and their regulation can be both conscious- and subconsciously processed and also positive as well as negative emotions can be regulated to a certain extent (Gross, 2007; Williams et al., 2009). Therefore, an increased emotional awareness is critical for enhanced ER. Up to now it is assumed that the applied ER strategies are also determined by personality traits and individual psychological capacity (Gross, 1998a).

5.2.3. Improved Financial Decision Making through Enhanced Emotion Regulation

A few studies from previous research have already shown that effective ER can improve financial decision making. Heilman et al. (2010) for instance, showed that ER can reduce loss aversion and thereby contribute to advantageous decision making. Sokol-Hessner et al. (2008) induced an intentional cognitive regulation strategy which emphasized co-called "perspective taking." The authors showed that this ER strategy, which can be understood as a form of cognitive reappraisal, mitigated physiological responses to losses relative to gains and also reduced subjects' loss aversion. Sütterlin and colleagues measured subjects' individual degree of inhibitory control, which is a physiological measure for ER capabilities. The authors found it to be negatively correlated with susceptibility to framing effects in a risky-choice task (Sütterlin et al., 2011). Similarly, Fenton-O'Creevy and colleagues measured the heart rate variability of professional traders in their daily environment. The authors found a significant relationship between effective ER and trader experience and argued that improved ER results from active trading experience (Fenton-O'Creevy et al., 2012). Further, in a study based on interviews, Fenton-O'Creevy and colleagues found that high performing traders (i) have a better awareness of their current emotional state and (ii) are also more sophisticated in down-regulating highly arousing states (Fenton-O'Creevy et al., 2011). Also the authors reported that new traders simply tend to avoid negative emotions, while experienced traders do not evade those negative arising emotions.

In conclusion, research so far has shown that the awareness of the own emotional state and the capacity to employ ER in states of high arousal overall is a considerable feature for financial decision making. ER can help to reduce emotions which might adversely affect decision biases and therefore even improve decision performance. However, how can a decision maker actually learn to improve his or her ER capabilities? Unfortunately, traditional learning approaches seem to fail when it comes to improving ER capabilities (Fenton-O'Creevy et al., 2012). In the context of ER, common problems of traditional learning approaches are (1) that learning ER and actually experiencing high levels of arousal are separated in time, and (2) that the subjects can get practically no feedback on their own capacity to regulate their emotions. In the following, we will address these problems by designing, implementing, and evaluating an IS artifact that aims at rewarding strong ER capabilities. In particular, we build on insights from cognitive neuroscience and provide users with a direct feedback of their current emotional state. Advances in cognitive neuroscience highlighted the influence of ER on emotional experience and the underlying visceral processes. For instance, Martin and Delgado (2011) supported the notion that effective ER reduces neural responses under risk, and henceforth results in more goal-directed decision making.

5.2.4. NeuroIS and Design Science Research

In the near past, the progress in cognitive neuroscience has also gained increasing interest from IS researchers (Dimoka et al., 2012, 2011; Riedl et al., 2010; Vom Brocke et al., 2013). As outlined by Dimoka and colleagues, the nascent field of NeuroIS is "drawing upon the theories, methods, and tools offered by cognitive neuroscience" (Dimoka et al., 2011, p. 687). This also includes psychophysiological tools such as electrocardiography and skin conductance measurement (Riedl et al., 2010). It is further argued that research in the field of NeuroIS has the potential to provide long overdue insight into the decision making processes of users interacting with IT. Certain insights were already gained by the application of NeuroIS experiments: For instance, Riedl and colleagues showed that deciding whether to trust an avatar induces less intense neurobiological processes than deciding whether to trust an actual person (Riedl et al., 2011). In another experiment, Riedl and colleagues reported that there are gender differences with respect to the activity of specific brain areas when deciding on the trustworthiness of eBay offers (Riedl et al., 2010). In a further experiment, Adam and colleagues showed that in electronic Dutch auctions the impact of time pressure on final prices is mediated by arousal, based on HR measurements (Adam et al., 2012). Also in the present study we will employ a derivative of the heart as a measure for arousal, which will be explained in more detail later.

While the number of empirical NeuroIS papers is constantly growing, the incorporation of cognitive neuroscience "is still in its infancy in IS design science research" (Vom Brocke et al., 2013, p. 2). In order to provide a framework for how tools and theories from neuroscience can be applied in IS design science research, vom Brocke and colleagues derived three specific application strategies (Vom Brocke et al., 2013). In this chapter, we focus specifically on Strategy 3 in the framework by Vom Brocke et al. (2013), i.e. on how neuroscience tools can be used as built-in functions of IT artifacts. In more detail, vom Brocke and colleagues argued that "IT artifacts with built-in neuroscience tools may even adjust to the affective state of the user" (Vom Brocke et al., 2013, p. 9). Thereby, IS design science research can build on progress in the fields of affective computing (Nacke et al., 2011; Picard, 1997, 2003) and neuroergonomics (Di Stasi et al., 2011; Parasuraman, 2003).

Picard (1997, p. 3) defines affective computing as "computing that relates to, arises from, or deliberately influences emotions." Picard et al. (2001) also highlights the importance of software which has the ability to sense and respond to the users' affective states based on physiological measures. Neuroergonomics is typically defined as "the study of brain and behavior at work" (Parasuraman, 2003, p. 5). In an interesting study, Di Stasi and colleagues showed in this context how eye-tracking devices can help to monitor operators' mental workload when interacting with hypermedia (Di Stasi et al., 2011). Additionally, previous research has employed physiological measures in order to find out how interacting with IT can induce strong levels of stress in the users (Riedl et al., 2012; Zhai and Barreto, 2006). One prominent concept in affective computing and also in neuroergonomics is biofeedback. Typically, for this form of feedback physiological parameters such as HR or SC are acoustically or visually displayed (Lehrer et al., 2000; Nacke et al., 2011; Ouwerkerk, 2011). Thereby, subjects get direct feedback on their own physiological reactions and processes; processes which are typically for subjects even below awareness (Dawson et al., 2011). It has been shown that biofeedback can increase the user's attention to the emotional state, which in turn can improve *interoception*, i.e. the conscious awareness of one's own physiological processes (Vaitl, 1996). Also, there is evidence that biofeedback can contribute to an alleviation of sufferings such as heart diseases and depression (Lehrer et al., 2000). In clinical studies, serious games with biofeedback are brought into use to train beginning doctors at reducing their level of stress (Wang et al., 2010). With respect to financial decision making, the electrics company Philips together with the Dutch bank ABN AMRO developed a biofeedback device for retail investors. The so-called "Rationalizer" is a device that "acts as a kind of emotion mirror in which the user sees reflected the intensity of his feelings in form of dynamic lighting patterns" (Djajadiningrat et al., 2009, p. 39).

5.3. Design and Method

In order to reward efficient ER strategies of decision makers, a NeuroIS tool is designed, implemented, and evaluated. Thus, this study serves as an example of how IS design science research can employ biofeedback as built-in functions of IT artifacts (Vom Brocke et al., 2013). The goal which is pursued with this tool is to put the decision maker in an interactive learning environment in which effective ER, assessed via biofeedback, is rewarded. The tool was developed by an international consortium with scientific backgrounds in information systems, computer science, finance, and psychology (www.xDelia.org).

5.3.1. Requirements

Importantly for IS design science research, the design decisions have to be well justified and based on existing research (Hevner et al., 2004; Peffers et al., 2008; Vom Brocke et al., 2013). Correspondingly, a set of specific requirements is defined (R1-R3). These requirements are based on the literature and serve as guidelines for the design process and are later used as criteria for the evaluation of the design artifact.

Requirement1 (R1): *The design artifact has to provide an engaging learning environment which can elicit arousal and is embedded in the context of financial decision making.*

Requirement 1 (R1) refers to the general nature of the created learning environment. From a learning perspective, it is important to highlight that "learning is maximized" when the learners are provided with an engaging environment (Dror, 2008). In contrast, "when the learning material is simply presented to the learners, they are passive and so learning is minimal" (Dror, 2008, p. 219). Moreover, down regulation of high levels of arousal—such as they occur for traders and private investors in real life—can only be actively practiced, when the user actually has to face a similarly arousing environment. According to Grandey, "the experience of both emotions and stress are known to be accompanied by a physiological state of arousal" (Grandey, 2000, p. 99). Therefore, the goal to create a design artifact based upon which ER can be actively practiced, can only be achieved when the users actually have to face an engaging learning environment which can elicit highly arousing states. Lastly, the general focus of our tool lies on rewarding ER in the context of financial decision making; therefore it was decided to embed the learning environment in a financial context. The reason behind this is that such a scenario may support the users in their strive to apply the learned skills in the game to a real trading context.

Requirement2 (R2): *The design artifact has to provide an environment in which effective ER is rewarded.*

The second requirement (R2) refers to our overall goal of rewarding the users with effective capabilities. In addition to merely providing the users with an arousing environment in which ER can be practiced, a core requirement for our design artifact is that effective ER is actually rewarded. By rewarding effective ER and punishing poor ER, the design artifact should help users to actively learn ER (Rolls, 2000). Both ER strategies reappraisal and suppression, when instructed, have been shown to be successful in down-regulating positive emotional states. There is also evidence that depending on specific traits, some subjects favor suppression to reappraisal and conversely (Volokhov and Demaree, 2010). Therefore it is left open to participants which strategy they want to use in order to regulate their arousal. Thereby we assume both ER strategies to be successful.

Requirement3 (R3): *The design artifact has to provide the user with live biofeedback in an unobtrusive and meaningful way.*

The third requirement (R3) refers to the biofeedback the user is given during playing the game. As mentioned before, a major problem with rewarding of effective ER is that users practically get no feedback on how successful they are at regulating their emotions (Fenton-O'Creevy et al., 2012). Our approach is to provide the users with real-time biofeedback on their emotional state by the usage of physiological measurements. This way, we intend to increase users' awareness to their own physiological state and thus improve their interoception. Certain requirements with regards to life biofeedback have to be met: First, from a technical perspective, life biofeedback systems should be designed as "unobtrusive and as unnoticeable as possible" (Ouwerkerk, 2011, p. 24). This assures that a user may also use them in daily life, such as in our case traders in day-trading centers or for private investors at home. In order to meet these requirements the system has to be easy and unnoticeable to wear. Second, from a user-interface perspective, the biofeedback has to be provided in a meaningful way i.e. the users should be able to actually draw useful information from the displayed biofeedback. Taken together, by providing the user with live biofeedback in an unobtrusive and meaningful way, the users can get direct feedback on their individual capacity to regulate their emotions during their interaction with the game.

5.3.2. Conceptual Idea

When turning to requirement R1, previous research has shown that learning through serious games can be engaging and can have a positive influence on the development of knowledge and skills (Anderson and Lawton, 2009). Generally, serious games aim at purposes apart from sheer entertainment (Corti, 2006; Legér et al., 2011). Serious games, which are repeatable, highly engaging, and also motivating can result in enhanced training activities and therefore in enhanced skill development (Corti, 2006). A major reason for the effectiveness of serious games as learning instruments is that "participants in a serious game must try something, even though they may not have complete or clear information about the best course of action" (Legér et al., 2011, p. 45). Following this argumentation, we decided to design and implement the design artifact as a serious game. The game is named *Auction Game* and, in line with requirement R1, is embedded in a financial context.

The Auction Game sets the player into the role of a trader who's goal is to earn money by repeated buying and selling a single stock in consecutive trading rounds. Each trading round gives the player information about the stock's real value in this round by displaying three sequential price estimates. These estimates correspond to the ratings of three independent analysts whereas the mean of the three price estimate represents the true value of the stock. Thereby, we follow the economic concept of common value signals (e.g. Oh, 2002). In each round the player has to calculate the mean of the three price estimates and to decide whether he or she wants to *buy* or *sell* the stock at a offered price. If the offered price is below (above) the true value of the stock, the player can realize a profit by buying (selling) the stock.[1] If the player opts for the wrong option, the payoff of this round is negative.

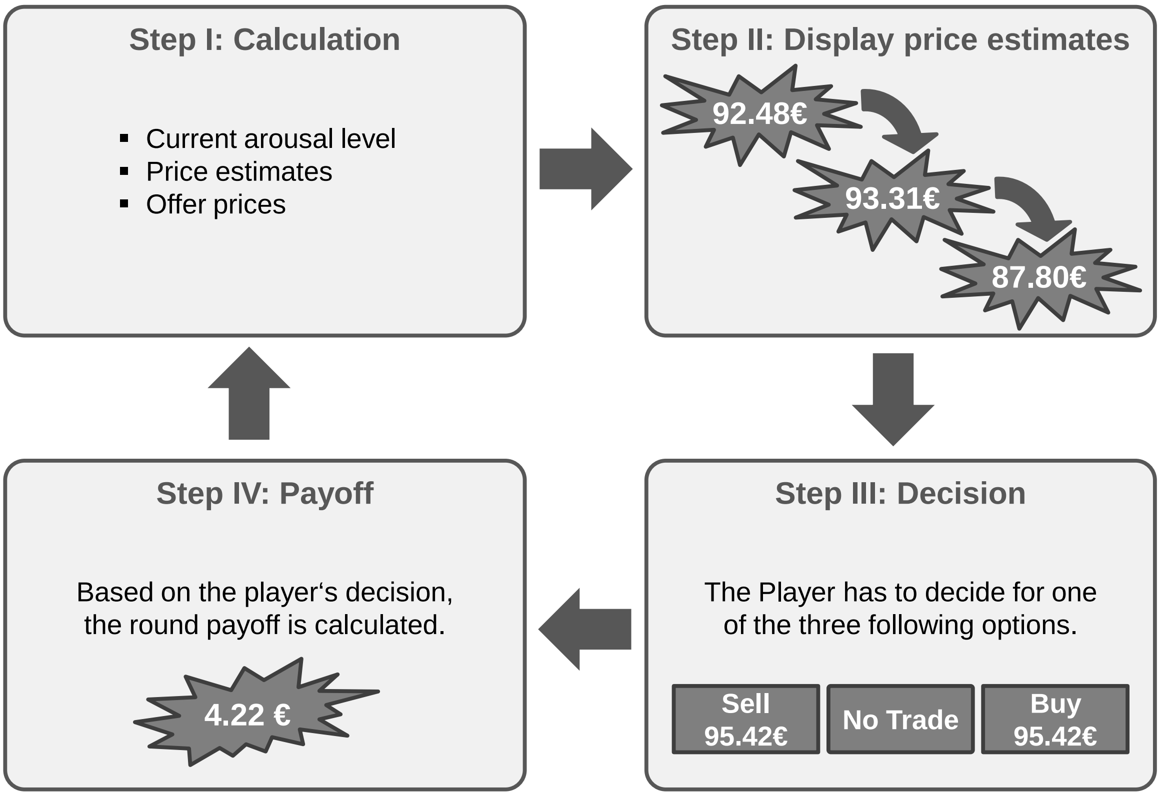


Figure 5.1.: Process of One Trading Round

[1]Short selling here means that the player can sell the stock without actually having it. This is a common procedure in financial markets.

A representative trading round is illustrated in Figure 5.1 . Each trading round comprises four steps (Step I-IV). Step I calculates the user's current level of arousal, the three price estimates for the stock, the true value of the stock, and an offer price. Later the player decides to buy or sell the stock for that offer price. Step II displays consecutively the three price estimates. In the example in Figure 5.1, the price estimates are €92.48, €93.31, and €87.80. Thus, the true value of the stock is €92.48+€93.31+€87.80/3 = €91.20 in this round. Step III sets the user into the position to decide for one of three options. In the example of Figure 5.1, the user can buy €95.42, sell for €95.42, or press the no-trade button. By pressing the so called no-trade button, the user can jump to the next round without having to suffer from a negative payoff. Conceptually, the no-trade button enables the user to escape an immediate decision and take a step back to calm down before returning to the active trade. If the user does not manage to choose one of the three options within a time limit of two seconds, he or she loses €5.00. By design this is the worst payoff a player can realize in a single round. Therefore, action should always be preferred to no action, as the user should never lose control over his or her actions. In Step IV, the gain or loss of the current round is displayed. In the example of Figure 5.1, the player decided to sell for €95.42. Since the mean of the price estimates (€91.20) is lower than the offered price (€95.42), the player makes a profit of €4.22. Afterwards the game returns to Step I with the next trading round.

5.3.3. Arousal Eliciting Game Elements

The Auction Game incorporates specific design elements with the aim to induce arousal into the users. First, the users get feedback subsequent to their decisions. Previous research has shown that being confronted with the positive and negative outcomes of one's own financial decisions can induce rewarding and aversive emotions (Astor et al., 2013; Bechara and Damasio, 2005). Therefore, with every decision a user has made, the Auction Game immediately provides a visually and acoustically highlighted feedback on whether she or he gained or lost money. Second, the Auction Game is designed to increase the general level of arousal by constantly putting the users under time pressure. Time pressure is generally known for increasing the decision makers' arousal and their willingness to take risk (Adam et al., 2012; Ku et al., 2005). In particular, in each trading round the user only has two seconds for submitting a decision. Similarly, each estimation cloud is displayed for only one second and this display time reduces to fractions of a second as the user progresses in the game. Taken together, the maximum duration of one round is five seconds. As it is essential to keep the user at constant levels of high arousal and to make the Auction game highly engaging (Kelly et al., 2007), the tool is structured into seven levels. The user's goal in the game is successfully complete the highest level and earn as much money as possible.

To earn money in the game the player has to make profitable decisions, allowing him to jump from one level to the next when he or she has achieved the current game level's profit goal. The profit goal increases by €30 in every new level. In case the user falls €10 below the current level's starting point, the game is finished. Conceptually, the user either accomplishes the final seventh level or an earlier game over results due to time or money constraints. Ideally the game runs for approximately 25 minutes and the user earns around €200 during the progression through the game.

Only four minutes are given the user to progress from one level to another, inducing an additional level of time pressure. Additionally, the background music in the game automatically adjusts to the user's current profit within each game level. The original beat of the background music is 120 bpm. It has been shown at several instances that background music is capable to impact subjects' level of arousal (Critchley et al., 2004). Due to this, we decided to increase the tempo of the background music, once the player has achieved 50 per cent and again when the user has achieved 75 per cent of the current level's profit goal.

Table 5.1.: Overview of Game Levels

Level	Element varying cloud estimates
1/7	Player's arousal is displayed but it has no effect on the game at all.
2/7	Player's arousal level affects the variance of estimates.
3/7	Estimation clouds move.
4/7	Estimation clouds become bigger and smaller in size.
5/7	Estimation clouds are same sized, but fake clouds with text start to appear.
6/7	Fake clouds with numbers start to appear. Distracting background images.
7/7	Estimation clouds become bigger and smaller in sizes again.

Table 5.1 summarizes the seven different levels of the game. With each game level game difficulty increases, making it more difficult for the player to make profitable decisions. With each level also new distracting feature are included in the game environment. Those comprise additional irrelevant clouds carrying false information, reduced display

time of the clouds, as well as auditory and visual distracting elements. For instance, starting in level 6, the background of the game interface shows arousing photos of the IAPS database (Lang, 1995) (see section Section 4.2.2 for a closer description). Also, the speed of cloud movement is correlated to arousal in higher levels.

5.3.4. Rewarding the Use of Emotion Regulation

The Auction Game employs physiological measurements in order to reward effective ER, as stated in requirement R2. It is focused in particular on down-regulation of high levels of arousal as those levels should be overcome and are often found to be correlated with maladaptive financial decision making (Adam et al., 2012; Ku et al., 2005; Kuhnen and Knutson, 2005). However, the here followed approach is not normative in a sense that we assume specific actions or strategies are always preferable to others. Our approach rather aims at extending the decision maker's toolbox (Gigerenzer and Selten, 2002) by improving his or her capabilities to down-regulate high levels of arousal when this is actually required for beneficial decision making. The player's goal in the game is to constantly keep her or his level of arousal low. As down-regulation of arousal shall be rewarded by the Auction Game, it is designed in the fashion that the player's current level of arousal (normalized on a scale from 1 to 5) influences the variance of the price signals. As by construction the variance of the price signals is connected to the player's current level of arousal. For instance, for an arousal level of 1, the price estimates would be €92.48, €93.31, and €87.80. For an arousal of 5, however, the variance of price estimates is much larger, which results in price estimates of €68.22, €79.21, and €126.17. Following, the game increases the difficulty for the player to calculate the mean of the pricing signals. By this setup, the player's level of arousal is directly connected to the game's difficulty. Therefore, in the game not only emotional awareness to the emotional state is boosted, even directly the down-regulation of arousal is rewarded. In following levels in the game additional elements are affected by arousal, such as the movement of the clouds on the screen. Summarizing, the better a subject is able to keep his or her arousal down, the easier the financial decision scenario in the game becomes. Therefore, the Auction Game is designed to directly reward effective ER in the context of financial decision making.

5.3.5. Employing Biofeedback

A central concept in the Auction Game is biofeedback, providing the user with a direct feedback on his or her current level of arousal. Cognitive neuroscience has shown that "the experience of both emotions and stress are known to be accompanied by a physiological state of arousal" (Grandey, 2000, p. 99), which in turn manifests in changes in physiology. In the context of IS, Riedl and colleagues have shown that the stress hormone cortisol is released when users experience "technostress" in response to a system breakdown (Riedl et al., 2012). While measuring cortisol levels is undoubtedly highly reliable for assessing arousal, the use of saliva samples is not suited for providing users with a continuously adjusting live biofeedback.[2] In order to meet requirement R3, we thus specifically focus on real-time measures. Skin conductance corresponds to the electrical conductivity of the human skin and reflects activity of the sympathetic nervous system, which activates the organism for fight or flight. While this signal is suitable for assessing the intensity of single (phasic) emotions, changes in the overall (tonic) level are rather inert (Dawson et al., 2011). The Auction Game, however, is by design characterized by a fast-paced decision environment and skin conductance measurements are thus not optimal in this context. Moreover, skin conductance is not innervated by the parasympathetic nervous system, which promotes recreation (Berntson et al., 2007). In contrast, the HR is a measure that reflects activity of both the sympathetic and parasympathetic branch of the ANS (Berntson et al., 2007). Moreover, sympathetic and parasympathetic activation is almost instantly reflected in changes in HR. The degree of interplay between the parasympathetic and the sympathetic nervous system provides an indication for a subject's ER capabilities (Sütterlin et al., 2011). Practically, the HR can be measured in an unobtrusive way by use of dry electrodes in a chest strap or a shirt. In contrast to sensors attached to the hand as for example for skin conductance or pulse measurement the chest strap allows a movement of the hand and will neither cause artifacts nor lose electrodes. Due to these characteristics, it was decided to use HR as the underlying parameter for biofeedback in the Auction Game.

[2] In this context, Ouwerkerk noted that "due to the large time lag of saliva sampling and obtaining the lab result, real-time monitoring of the hormone levels is currently not feasible in a daily life situation" (Ouwerkerk, 2011, p. 25).

5.4. Implementation

Based on the requirements and design decisions outlined in the last section, we now present how the Auction Game was implemented and demonstrated in practice. The implementation followed an iterative process (Hevner et al., 2004; Peffers et al., 2008) which involved demonstration to real practitioners at trader and investor shows, as well as play-testing calibration with student testers. Insights from the demonstration directly fed back into the implementation.

5.4.1. Architecture of the Game

The Auction Game is based on a modular and dynamic architecture, which can be adjusted to include further game elements by modifying an XML configuration file. In particular, the Auction Game can be used with measurement devices from different manufacturers. A screenshot of the game and further details on the game mechanics are provided in the following.

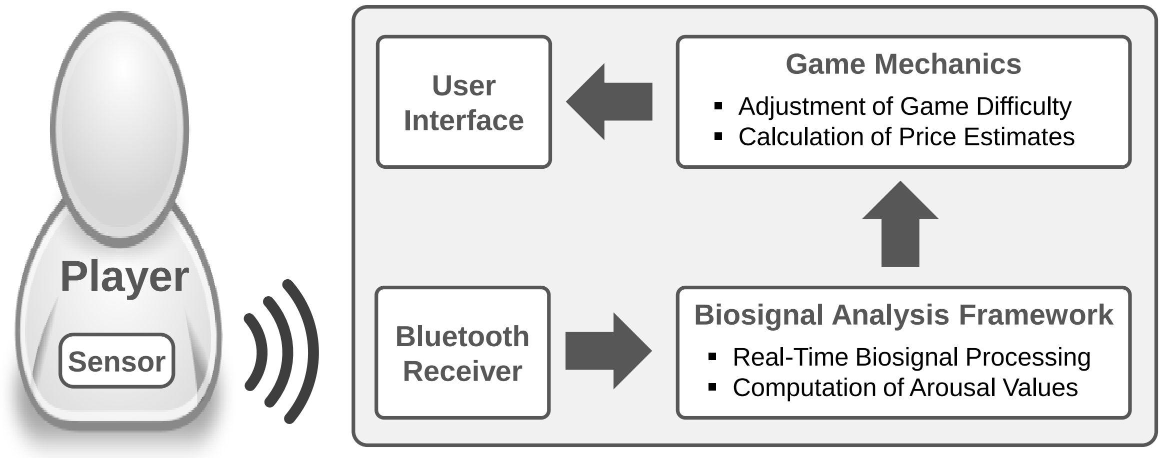


Figure 5.2.: Schematic Overview Over the Game Architecture

The Auction Game architecture is schematically depicted in Figure 5.2. The ECG device was chosen in consideration of R3 to be as unobtrusive as possible. More specifically, the player wears a dry electrode chest-belt and a sensor that transmits the user's ECG wirelessly to a Bluetooth receiver. A biosignal analysis framework then processes the ECG data, computes the arousal values and feeds them into the game in real-time.

The game constantly adjusts the level of game difficulty, calculates the price estimates, and updates the user interface.

5.4.2. Arousal Value Computation

As outlined in the design section, the computation of arousal values is based on HR. To connect the physiological sensors to the game, the *xAffect* framework was used. This software environment provides a modular open source framework for offline and online analysis of biosignals. It can be used as a middleware between physiological sensors and 3rd party software such as the Auction Game. After receiving the ECG signal, QRS detection is performed using the OSEA algorithm (Hamilton, 2002). The ECG is then decomposed into characteristic deflections referred to as P, Q, R, S, and T waves. The R peak is the most characteristic peak in the ECG signal and corresponds to the bulk of ventricular myocardium activity, i.e. the activity of the heart chamber muscle (Berntson et al., 2007). The QRS algorithm is used to detect these R peaks, based on which HR is computed. Irregular beats are excluded from further analysis using the algorithm proposed by Clifford and colleagues (Clifford et al., 2002).

Before the actual trading task starts, there is a five minute rest period in order to assess an individual baseline level of arousal (cf. Sütterlin et al., 2011). The arousal values in the game are then derived from the HR in relation to this baseline period. Sympathetic activity tends to increase HR, while parasympathetic activity decreases HR. In the game, an increase in HR compared to the initial baseline period, results in an increase in the computed arousal. To avoid that respiratory sinus-arrhythmia is reflected in the arousal value, the mean value over the last 5 heart beats is used for arousal computation (Berntson et al., 2007). Humans have limited information processing capabilities-particularly in fast-paced environments. Reducing the amount of information to a limited number of categories is thus essential to facilitate effective information processing (Miller, 1956). Previous research has shown particularly that reductions to five or seven categories are effective (e.g. Lozano et al., 2008). In order to provide the users with biofeedback in a meaningful way (cf. R3), the arousal parameter in the Auction Game can thus only take on five different integer values (1 to 5). A value of 5 corresponds to the highest level and is reached if the current HR is more than 15.00 per cent higher than in the initial rest period. A value of 4 corresponds to the second-highest level and is reached if the increase in HR is between 11.25 per cent and 15.00 per cent. Finally, a value of 1 corresponds to an increase of 0.00 per cent or lower. The threshold values were calibrated based on an iterative implementation process with student and real investor trial sessions. Moreover, the range of values is in accordance with the levels reported in previous research (Adam et al., 2012; Smith and Dickhaut, 2005). Figure 5.3 depicts the generated unisens.xml with information about a participants' ECG, triggers for each heart beat and the calculated heart rate.

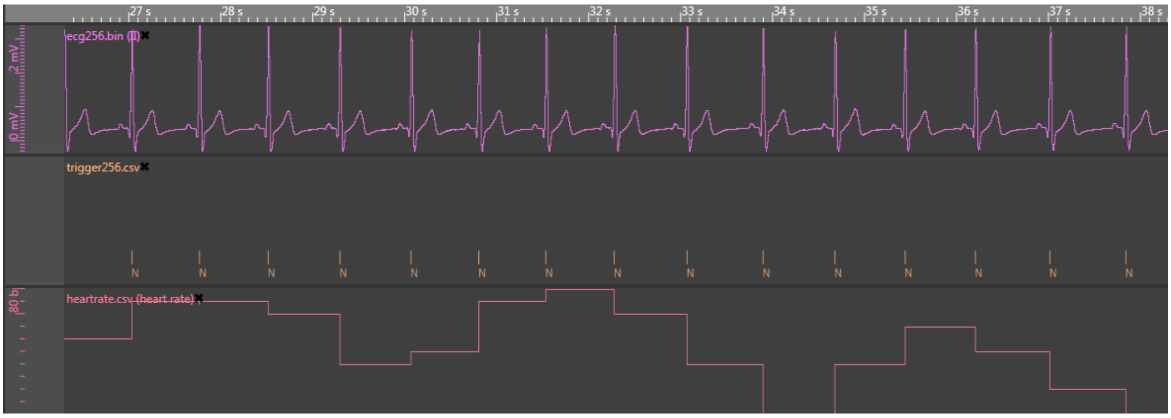


Figure 5.3.: Unisens.xml with ECG, Triggers for Heart Beats and Calculated Heart Rate

5.4.3. Display of Arousal Values

In the Auction Game, the arousal parameter is displayed to the user by means of an arousal meter that visualizes the user's current emotional state (see Appendix). Meters are frequently used in user interface design to display important indicators in an intuitive and meaningful way (cf. R3, see (Ariely and Loewenstein, 2006; Caria et al., 2007) for a similar approach). The arousal meter visualizes the five different levels of arousal with colors ranging from green (1) to red (5). This approach is similar to the light patterns used in the Philips Rationalizer which were designed to make the arousal levels "intuitively clear" (Djajadiningrat et al., 2009, p. 44).

In order to objectively determine which game elements the users are paying attention to during the game, a Tobii T60 eye tracking device was used when demonstrating a prototype of the game to six students. The results revealed that users in general paid attention to the arousal meter. However, when the decision scenario became more complicated, the users hardly paid attention to the arousal meter. The users stated that this was due to lack of time during fast-paced decision making. Based on these results, the visualization of arousal values was extended to also include the cloud estimations so that the important information is presented at the attention focus point. More specifically, the cloud estimates were implemented to change their color according to the current level of arousal. This feature was found to be very useful by student testers as well as real traders and investors in subsequent demonstration sessions.

5.5. Evaluation

In order to evaluate the Auction Game, we conducted two laboratory experiments (Evaluation Study I and II). The evaluation measures as well as the design and procedure of the experiments are outlined in the following. As argued by Hevner and colleagues, "a design artifact is complete and effective when it satisfies the requirements and constraints of the problem it was meant to solve" (Hevner et al., 2004, p. 85). Correspondingly, the requirements (R1-R3) derived in the design section are now used as criteria for the evaluation and thus for the design of the experiments.

5.5.1. Experimental Design

The general aim of Evaluation Study I and II is to evaluate whether the Auction Game can in fact induce high levels of arousal (R1) and whether effective ER is rewarded (R2). Moreover, by activating and deactivating biofeedback and its impact on game difficulty, it was evaluated whether the display of biofeedback was meaningful in the sense that it helped the users to achieve a higher decision performance (R3).

Table 5.2.: Overview on Evaluation Study I and Study II.

	N	Participants in treatment	Physiological Measurement	Biofeedback	Influence on Game Difficulty	Age	Female[3]
Evaluation Study I	36	BF: 19	YES	YES	YES	23.39 [20-28]	12
		NBF: 17	YES	NO	YES		
Evaluation Study II	68	BF: 44	YES	YES	YES	23.39 [20-28]	16
		NI: 24	YES	NO	NO		

The core parameters of the two experiments are summarized in Table 5.2. Both studies are based on between-subjects designs with a total number of 36 and 68 subjects, respectively.[4] In the biofeedback treatment (BF), the subjects are provided with a direct feedback on their emotional state. In the no-biofeedback treatment (NBF), subjects do not gain any direct information on their emotional state. In both treatments, however, the arousal level has a direct impact on game performance (see design section). Thus, in both treatments the level of arousal is positively correlated with the game difficulty. Participants in NBF and BF receive the same instructions on how emotional arousal influences game difficulty, except that the NBF version does not get any information on the arousal meter and the adjusting color of the clouds, since these elements do not occur in their game version. Figure 5.4 in the Appendix depicts screenshots of the different treatments. Finally, in the no influence (NI) treatment, subjects play the game in a mode where neither the emotional state is indicated nor does it influence the game whatsoever. For this group also the instruction material differs slightly: Participants of the NI treatment only received the information that “paying attention is an important task to regulate your emotions”, without referring to arousal. It is important to highlight in this context, that the arousal influencing the game can only increase game difficulty. This means that subjects in the NI treatment played a game in which the trading task is never more difficult than it is in the BF treatment. Therefore, it is interesting to analyze, whether biofeedback and thus an increased sensitivity for ER in fact has a positive impact on decision performance in the Auction Game.

5.5.2. Game Mechanics

The Auction Game was developed using the Unity 3D Pro game engine[5]. The game is played in a 2D environment, where price estimates are presented inside colored cloud drawings. To depict a sense of progress through the game, every level has a different background picture of the sky.

[3] An ANOVA indicates no significant difference in decision performance between male and female subjects ($F(1, 102) = 1.181$, $p = .280$).

[4] Originally, 46 subjects participated in Evaluation Study I and 80 subjects participated in Evaluation Study II. Due to difficulties with the wireless data transmission we had to exclude 10 subjects from Study I and 12 subjects from Evaluation Study II. This was necessary, because for these subjects no ECG was recorded—and hence no arousal values could be calculated—or the signal was inverted.

[5] The Unity 3D Pro software environment provides one of the world’s leading game engines for professional video games. For further information, please refer to http://www.unity3d.com.

Figure 5.4.: Game Screen of the Auction Game

Figure 5.4 displays a screenshot of the Auction Game. On the top-left side of the screen, the remaining time for the current level is displayed. The player can see his or her individual arousal level indicated on the meter in the right top corner, as well as by the color of the clouds (green, yellow, and red). The profit goal and total money earned are presented on the meter at the bottom-right side of the screen. Decisions can be made by clicking on the buy, the sell, or the no-trade button at the bottom of the screen. Note that, in contrast to the illustration in Figure 5.4, the clouds appear sequentially in the game and that the location of their appearance on the screen is random. The decision terminal does not get activated before the last cloud got indicated. Every profitable decision will reward the player with a certain amount of money, while a non-profitable decision will reduce the player's earning and take him or her further away from the current level's profit goal. Figure 5.5 displays screenshots of the two treatment groups of Evaluation Study I.

Figure 5.5.: Game Screens of the two treatment groups of Evaluation Study I; with and without biofeedback (cloud colors and arousal meter).

Before the game starts, the instructions on how to play the game are displayed. Moreover, the player can choose to go through a tutorial. The tutorial explains the principle of the game and introduces its different elements step by step. The tutorial should be played the first time the player gets in contact with the game, but it can be skipped if the player already knows the game. Starting from level 6, affective pictures from the IAPS database are randomly displayed to distract the user and further induce arousal. Thereby, we selected particularly pictures with high arousal scores while excluding disgusting pictures[6].

5.5.3. Measurement Devices

Due to the flexible software architecture of the biosignal analysis framework, the Auction Game can be connected to a variety of measurement devices. In the evaluation studies described in this chapter, we used two different types of measurement devices. The first device is called ekgMove and is produced by the company Movisens. It is a sensor on a chest strap with dry electrodes. The strap is attached directly on the subject's chest (comparable to the ones used during sport exercises). The assessment is performed using Bluetooth and therefore the chest strap and sensor are very comfortable to wear

[6]In particular, pictures #1505, #2080, #2091, #2154, #2156, #2158, #2216, #2274, #2303, #2332, #2340, #2341, #2345, #2598, #5623, #5830, #5831, #8001, #8050, #8060, #8065, #8116, #8117, #8118, #8130, #8220, #8230, #8231, #8232, and #8467 of the IAPS database were used.

as there are no wires required.[7] The second device is called Varioport-e and is produced by the company Becker Meditec. In contrast to the ekgMove, it requires a constant cable connection of the electrodes to the PC. The Varioport-e system was used for measuring the ECG of eight subjects in Evaluation Study I. This demonstrates that the Auction Game can be used with measurement devices of different producers.

5.5.4. Measures

The evaluation is based on a set of specific measures. First, the users' current level of arousal is assessed on a scale from 1 to 5 by means of ECG measurements as outlined in the implementation section. Second, we measure each user's decision performance in the Auction Game. More precisely, a user's individual decision performance is defined as the percentage of decisions taken correctly out of all decisions. Pressing the no-trade button is defined here as a correct decision, since it always prevents against losing € 5.00 when not choosing one of the other options. Third, we assess to which extent ER strategies are consciously applied by individual users. Therefore, we use the ER questionnaire by Gross and John (Gross and John, 2003; Abler and Kessler, 2009), which focuses specifically on the strategies cognitive reappraisal and suppression. The ERQ is characterized by high reliability, high discriminate validity, and only little correlation with the dimensions of other psychological questionnaires (Scheibe, 2011). Both strategies assessed with the ERQ could been shown to be beneficial for regulating positive emotional states and negative emotional states to a certain extent. Therefore, we use a single measure that equally reflects both strategies as an indicator for consciously applying ER strategies; in the following denoted as ER score. Due to experimental constraints the ERQ was carried out in a different chronology in the two studies and subjects' average scores vary. Nevertheless, the results are invariably robust against controlling for this issue. See Appendix B for a more detailed description, an analysis with independently normalized ER scores and also a factor analysis carried out with the ERQ data set of the present experiment. Fourth, in addition to using the ERQ, we also directly asked the subjects of Evaluation Study I which strategies they applied in order to down-regulate their emotional arousal and analyzed the effectiveness of these strategies.

[7] In fact, one student left the laboratory after the experiment without noticing that she was still wearing the chest belt and the sensor.

5.5.5. Experimental Procedure

Both experiments were conducted at KIT. Evaluation Study I was conducted in late 2011 and Evaluation Study II in early 2012. The ORSEE software environment was used to recruit participants from a pool of university students (Greiner, 2004). In the first study a constant conversion of game Euros earned into real cash was used, which was paid directly after subjects had finished the game, according to their performance. In the second study the game was played within a set of games (which will not be described here in detail) and the payment was randomly chosen according to the performance in one of the games. Thus, in both studies subjects had a high incentive to perform to their best in order to earn money.

Subjects were randomly seated in the laboratory and the use of the sensors was explained during the registration. Furthermore subjects received an envelope which contained the number of their work station and their anonymous identification number. In order to reduce distractions, each participant sat in his or her own cubicle with noise-cancelling headphones and was therefore completely separated from the other participants. After the instructions were read via headphones to the subjects they started playing a tutorial which walked them slowly through the game mechanisms. Subjects had to complete the training mode successfully before a five minute rest period started and they could proceed with the game session.

5.6. Evaluation Results

In this section we present the results of the two evaluation studies along with the three requirements introduced in the design section. Altogether, subjects took around 79 decisions on average before the game stopped, with 21 decisions being the fewest and 177 being the most. The no-trade button was used in around 10 per cent of the decisions and subjects needed on average 1.15 seconds to take a decision once they had received the three price estimates. Of all the 104 subjects who participated in the two studies 18 managed to complete the game.

5.6.1. Evaluation Results for Requirement R1

In order to examine the engaging impact of the Auction Game, the subjects' arousal level and HR during the game were constantly assessed. The arousal parameter reveals that the game in fact induces arousal: the average arousal level, which can take on values from 1 to 5, is $M = 3.272$, ($SD = 1.285$). For almost all subjects (97 per cent) the highest arousal level of 5 was reached at some point of the game, and for the majority of subjects (65 per cent) all possible values from 1 to 5 were encountered during the course of the game. Subjects' HRs during the game are on average 11 per cent higher compared to the baseline period (ΘHR) and for the large majority of subjects (88 per cent) the average HR is higher during the game period compared to the baseline period. Figure 5.6 and Figure 5.7 illustrate subjects' average arousal and HR during the game relative to the baseline period.

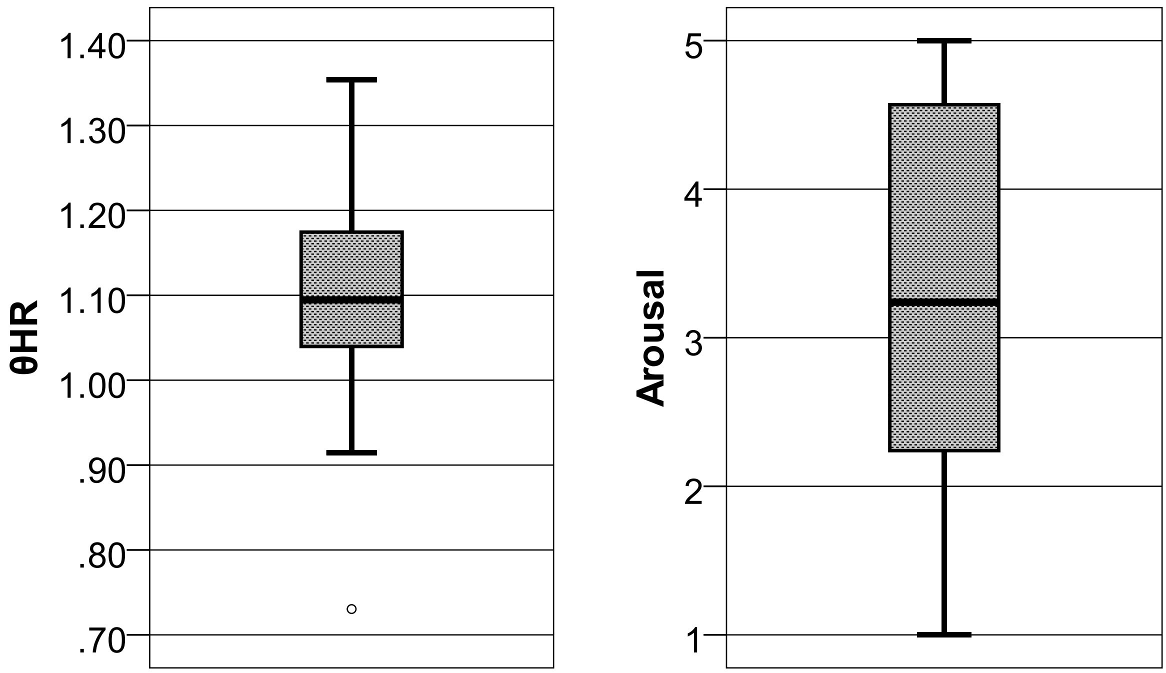


Figure 5.6.: Subjects' Average HR and Arousal
Note: The correlation between HR and arousal does not map perfectly, since ΘHR values smaller than 1.00 result in arousal values of 1 and ΘHR values exceeding 1.15 result in arousal values of 5.

These increases in HR are remarkable with respect to the fact that the subjects did not engage in any physical exercise, but simply played an engaging serious game. This

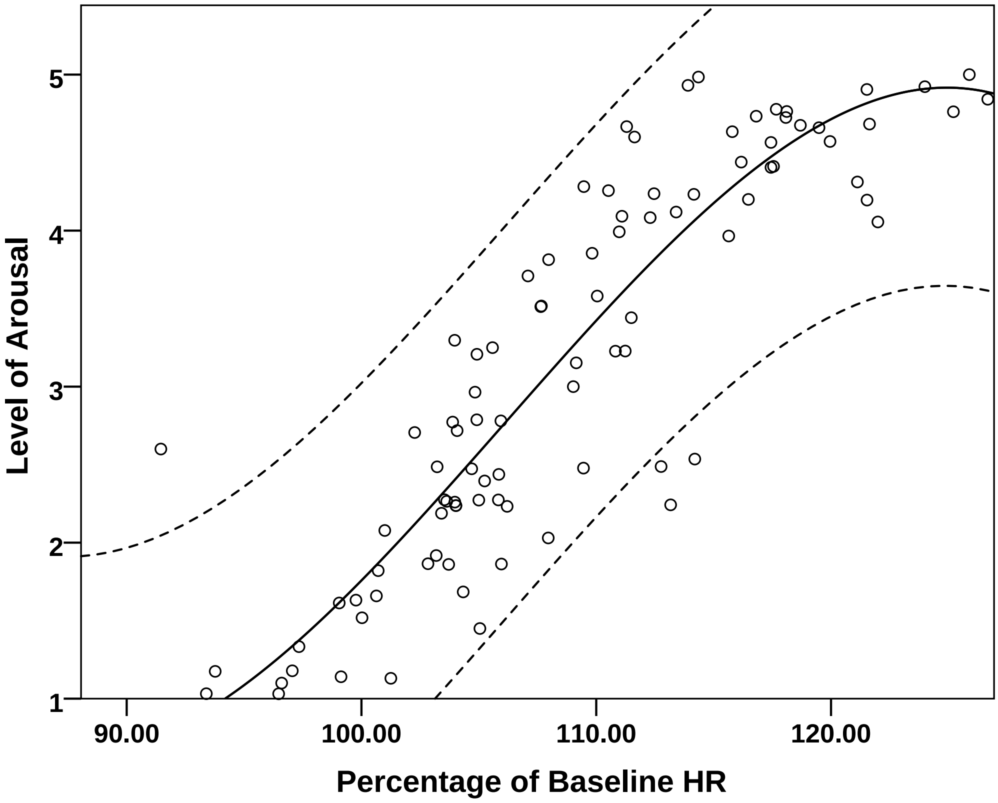


Figure 5.7.: Correlation of Subjects' Average HR and Arousal

is also supported when comparing our results to other studies. Adam and colleagues also employed ΘHR as a measure for physiological arousal in fast dynamic auctions, but report slightly lower values (Adam et al., 2012). Smith and Dickhaut list typical HR responses to induced idiosyncratic emotions (Smith and Dickhaut, 2005). The reported scores average for the strongest emotions around 4 to 7 beats per minute above baseline. This is lower than the average HR during the Auction Game, which results on average in 8 beats per minute above baseline.

In Evaluation Study I, we additionally asked the subjects to fill out a questionnaire and report the affective states they had experienced during the experiment. The highest reported emotional states were tension (M = 4.78; SD = 1.290), joy (M = 4.08; SD = 1.592), and anger (M = 3.97; SD = 1.828). Additionally, subjects were asked to express their overall impression of the game in a free text field. The majority of the subjects reported that they liked the game and also felt highly aroused while playing it. They liked to pick up the concept to regulate their emotions in order to ease game difficulty. These self-assessments are in line with our findings from physiology that the game is capable of inducing arousal. Based on the physiology and questionnaire results, we conclude that in line with R1 the Auction Game provides an engaging learning environment which can elicit arousal and, by design, is embedded in the context of financial decision making.

5.6.2. Evaluation Results for Requirement R2

In order to test whether the game rewards effective ER, we analyze whether those subjects who managed to down-regulate their arousal are in fact more successful in the game. As depicted in the left part of Figure 5.8 subjects' average decision performance decreases with increasing levels of arousal. Correspondingly, the right part of Figure 5.8 shows that the average arousal level is lower for those subjects, who manage to successfully reach the final game level ($n = 18$) compared to the other subjects.

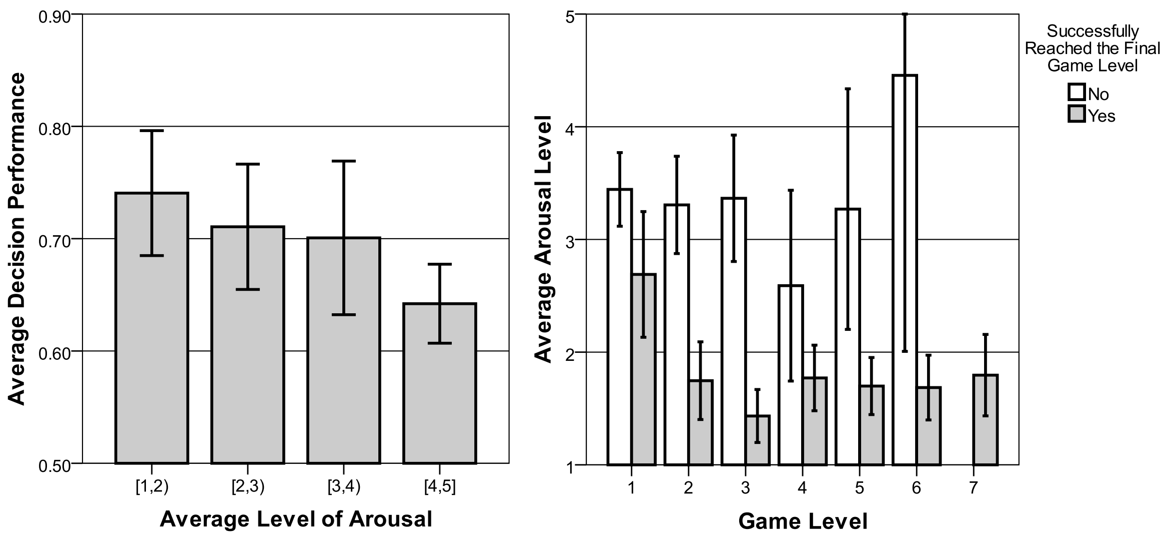


Figure 5.8.: The left bar chart illustrates subjects' average decision performance depending on their state of arousal. The bar chart on the right indicates subjects' average arousal during the game levels (Error bars: 95 per cent confidence interval).

In order to test this relationship, we conduct an OLS regression with *arousal* and the *ER score*, which is summarized in Table 5.3. In this regression we also take into account whether subjects participated in Evaluation Study I or II *(dummy study II)*, in order to control for potential slight differences in game and treatment design, and whether subjects were assigned to the NBF treatment, which only existed in Evaluation Study I *(dummy NBF)*. The regression confirms that arousal has a significant negative influence on decision performance ($B = -.032$, $SE = .009$, $t = -3.370$, $p < .01$).

Table 5.3.: Regression results for subjects' decision performance on arousal and ER ($n = 80$) (Employing the *ER score*).

	Decision Performance				
Independent variables	**B**	**SE**	***t*-Stat**	***p*-value**	**Sig.**
arousal	-.032	.009	-3.370	.001	**
ER score	.041	.019	2.132	.036	*
dummy NBF	-.091	.034	-2.640	.010	*
dummy study II	-.034	.034	-0.982	.329	
c (constant)	.858	.068	12.561	<.001	***

* $p < .05$, ** $p < .01$, *** $p < .001$

Another opportunity to assess whether effective ER strategies are rewarded while playing the game is to analyze the results of the ERQ, which is used to determine subjects' consciously employed tendency to regulate their emotions. As can be seen in Table 5.3, the regression reveals a positive impact of the ER score on decision performance ($B = .041$, $SE = .019$, $t = 2.132$, $p < .05$). Further robustness checks of the results can be found in the Appendix B.2. Interestingly, subjects scoring high on ER tend more often to hit the so called "no-trade button" and thereby escape the € 5.00 penalty ($n = 80$, Pearson's $r = .213$, $p = .058$). However, this effect is only marginally significant.

Moreover, in Evaluation Study I we used a free text questionnaire in order to ask the users what kind of strategies they used to actively down-regulate their arousal. Out of the 36 participants, 21 stated that they tried to regulate their breathing in order to regulate their arousal. Common answers were: "I tried to breathe calmly" and "I concentrated on breathing." Two subjects tried to close their eyes for a moment when they realized that they were too aroused, in order to take a step back from active trading and relax before returning to it. Six subjects tried to "think of something different." These strategies are very similar to professional meditation techniques as, for instance, applied in mindfulness interventions which is often linked to ER (Kabat-Zinn et al., 1992). Active-breathing and closing-eyes lead to increased average decision performance in the game. As additional result, we find that subjects experience of subjective "frustration, when taking a wrong decision", positively correlates with arousal ($n = 36$, Pearson's $r = .374$, $p < .05$). With respect to R2, we conclude that the Auction Game rewards effective ER with a high decision performance in the game and is thus suitable for helping users to actively train ER.

5.6.3. Evaluation Results for Requirement R3

By design, biofeedback in the Auction Game is based on unobtrusive measurements (cf. design section). In order to test, whether biofeedback is also provided in a meaningful way, i.e. whether the users can actually draw useful information from it, we analyze subjects' decision performance with and without biofeedback. In Evaluation Study I, one treatment group played the Auction Game with biofeedback (BF) and one treatment group played the Auction Game without biofeedback (NBF). In other words, subjects in the NBF treatment did not see the arousal meter and color adjustments of the clouds. It is important to note, however, that the positive correlation of arousal and game difficulty remains unchanged, only the feature of biofeedback is controlled for. As a first descriptive result it is interesting to note that subjects in the BF treatment stated that they do not think that the biofeedback helps them either to "become aware of their current emotional state" ($M = 2.65$; $SD = 1.656$), nor to "help them with making better decisions" ($M = 1.82$; $SD = 1.074$). However, a t-test confirms that subjects of the BF treatment achieved a better decision performance than the subjects of the NBF treatment (.749 vs. .658, $n = 36$, $t(34) = 2.530$, $p < .05$). This is also confirmed by the regression ($B = -.091$, $SE = .034$, $t = -2.640$, $p < .05$). Taken together, these results demonstrate that biofeedback helped subjects to increase their decision performance in the game. In Evaluation Study II, we introduced a no-influence treatment (NI) in which the biofeedback was neither displayed, nor did it influence game difficulty. In other words, the two core features of the game "live bio feedback" and "arousal influencing game difficulty" were deactivated in the NI treatment. In this context, it is important to note that the correlation of arousal and game difficulty can only make the game harder to play. Therefore, in absolute terms, subjects in the NI treatment played a game in which the trading task is never more difficult than it is in the BF treatment. However, if subjects can employ the biofeedback profitably this might mitigate or even offset this effect. The results of Evaluation Study II show that subjects in the BF treatment performed better in the Auction Game than those subjects who were in the NI treatment (.688 vs. .629, $n = 68$, $t(66) = 1.985$, $p = .051$); however, this effect is only marginally significant. In other words, those subjects who knew that their arousal level influences game difficulty achieve a higher decision performance—even though playing a more difficult game. It therefore seems plausible that the positive effect of biofeedback offsets or even exceeds the negative effect of the correlation between arousal and game difficulty. It is important to note, however, that we cannot control for game difficulty here, as it is by design endogenously connected to arousal. Based on our study, we thus cannot draw general conclusions on how biofeedback impacts decision performance in general. We will return to this point in the discussion.

In summary, we conclude that the users were provided with biofeedback in a meaningful way in the sense that it helped them to perform better in the Auction Game. This is also supported when comparing the overall arousal level in the two treatments. The overall arousal level was significantly lower in the BF treatment than it was in the NI treatment (2.871 vs. 4.030, $n = 68$, $t(66) = -3.820$, $p < .001$). Thus, the subjects were able to draw information from the biofeedback and down regulate their current level of arousal. Based on the results of Evaluation Studies I and II, we conclude that in line with R3 the Auction Game provides the users with live biofeedback in a meaningful way which is, by design, based on unobtrusive physiological measurements.

5.7. Discussion and Conclusions

5.7.1. Managerial Implications

The Auction Game was designed and implemented in close correspondence with practitioners from the banking and finance industry. Therefore, it is particularly relevant for professional traders and private investors who want to improve their ER capabilities. In this regard, the Auction Game has already drawn attention at several international trading and investment conferences. Especially during stressful periods traders and investors are highly motivated to remain level-headed and improve their ER capabilities (Fenton-O'Creevy et al., 2011). The Auction Game provides market participants with a tool that can help them to train stressful periods and actively practice ER. Banks like ABN AMRO, Barclays, and Saxo Bank have recently become aware of their customers' interest in de-biasing and ER training. In this context, a growing number of banks strive to offer their customers specific training services for skill development. The

Auction Game and similar biofeedback approaches can thus be included as intervention elements. The Philips Rationalizer was an important first step in this direction (Djajadiningrat et al., 2009). Similar to the Auction Game, future trading systems will also directly incorporate biofeedback into their trading interfaces. But also beyond the scope of skill development and training, biofeedback will play a more and more important role for the designers of trading interfaces.

In the near future, shirts with built-in dry electrodes will come into the market and technical progress already allows wireless recording and real-time processing of ECG data. A prominent example for unobtrusive skin conductance measurement is the *Affectiva Q Sensor*, which is a wearable sensor for long-term assessment in the field (Poh et al., 2010). Soon it will be possible to constantly measure and process a wide range of physiological parameters in real-world decision scenarios instantaneously and integrate them into the trading interfaces; e.g., at day-trading centers and also for private investors at home. Thus, it will be possible to provide the decision makers with a highly sophisticated live biofeedback on their current emotional state, to immediately warn them in critical situations, and support them with improving their ER capabilities. In this context, it will also be very interesting for traders, investors, and consumers, to match arousal to their decision performance on a longer time base. The continuous assessment of the emotional state during periods of strong and poor decision performance could help subjects to understand how their own arousal and decision performance are interlinked. Moreover, biofeedback games like the Auction Game can then be used to help the subjects to regulate their arousal to an individually optimal level-also beyond the scope of financial decision making.

While there is a growing number of related studies in the fields of Neuroergonomics and affective computing, the use of tools from cognitive neuroscience in design science research has only just begun (Vom Brocke et al., 2013, p. 2). By applying methodologies from neuropsychology and psychophysiology to information systems research, the new field of NeuroIS provides long overdue insight into the decision making process of human individuals when interacting with modern IT (Dimoka et al., 2012, 2011). Thereby, one major goal is to support human decision makers. In this sense, the Auction Game is a use case for how information systems can incorporate physiological and neurological biofeedback in order to improve human decision making. Applying ER strategies in the context of information systems research is not only limited to decision making alone. It can also be helpful for well-being, learning, and health. Riedl and colleagues showed that IT users are exposed to “Technostress” (Riedl et al., 2012). Down-regulating arousal can help subjects to reduce the impact of stress and, thus, to maintain and improve health (Gross, 2009). Therefore, ER training and the integration of biofeedback into information systems are also highly relevant from a management perspective as it may help managers to reduce their employees overall stress levels and thereby increase productivity.

5.7.2. Limitations and Future Research

There are several limitations that exist in this study. First, the presented Auction Game was designed to reward down-regulation of arousal. While it was shown that in many scenarios arousal can impair decision making (Ku et al., 2005; Kuhnen and Knutson, 2005; Peterson, 2007), there are also scenarios where it might be beneficial to up-regulate arousal to an optimal level and maintain that level (cf. Flow Theory (e.g. Nacke and Lindley, 2008), Yerkes Dodson Law (Hebb, 1955)). In this respect it is important to note that we do not pursue a normative approach in the sense that low arousal is always preferable. We rather aim at improving the user’s capacity to reduce high levels of arousal when he or she aims at doing so. For future research the design artifact could easily be adjusted with the goal to train up-regulating arousal or even target an optimal level of arousal. Subjects’ trading data from the field could then be assessed in order to detect an individual optimal arousal level, where performance is highest. Then, similar to how athletes warm up before sport events, traders could warm up before they start with their actual task, in order to reach their optimal arousal level.

A second limitation is that, due the fast-paced decision environment and further reasons outlined in the design section, the current calculation of arousal is based on HR measurements solely. Dependent of the particular context and focus, future research should employ further physiological parameters, e.g., skin conductance or electroencephalogram (EEG). Both of these measures are well known physiological proxies for emotional processing. Also noncontact monitoring of arousal has been successfully employed in recent studies (Nunamaker et al., 2011). A combination of several parameters will produce a more accurate and robust computation of arousal.

A third limitation arises from the fact that we varied two features between the treatment groups in Evaluation Study II, the connection of game difficulty to arousal, but also the display of biofeedback. In both studies we found biofeedback to be meaningful in the sense that it helped users to achieve a higher decision performance. It is important to highlight though that we cannot directly draw inferences with respect to whether immediate biofeedback also generally increases decision performance. By design, arousal and game difficulty are combined in our approach. The question, whether biofeedback is beneficial for users beyond the use case of ER training is, however, highly relevant for IS design science research.

Fourth, as mentioned earlier, decision performance was assessed by the percentage of decisions which users have taken correctly out of all decisions, including the user's conscious decision to hit the so called no-trade button. While this measure is highly correlated with other measures for game performance, such as maximum money earned ($r = .734$, $p < .001$, $n = 104$) or total number of decisions taken ($r = .631$, $p < .001$, $n = 104$), it cannot be inferred that the presented results are invariably robust against these other measures. However, decision performance as it was defined is in this context is the most suitable measure as it positively appreciates the user's conscious decision to actively turn away from trading in order to calm down.

Fifth, as the Auction Game was designed within a research project and as a study tool, it should not be considered as a fully fledged game from a rather gaming-oriented perspective. For instance, game difficulty in the first level should be refined, as a significant proportion of the participants already failed in the first couple of minutes. Further, possibly due to the lack of diversion in the game the Auction Game's capabilities towards a long term skill development of ER must be questioned. While we found in this study the ER score to increase decision performance, it remains unclear to what extent the tool can be used to improve the two ER strategies reappraisal and suppression over an extended period of time. In that respect a longitudinal study (not described here in detail) within the project *xDelia* lead to mixed findings concerning how and whether the trait variables cognitive reappraisal and suppression can be improved over a longer period of time. While the tool accomplishes its requirement to punish poor ER skills in a one term period, it lacks the necessary complexity in order to maintain its functions of punishing poor ER and high arousal when often repeated. Nevertheless, an adaption of the game to couple arousal also on other, potentially more sophisticated and alternating mechanisms of game difficulty, could potentially mitigate these drawbacks.

For future IS design science research it will be interesting to investigate to what extent biofeedback environments can (1) be of valuable decision support for the users and (2) contribute to a long term skill development of effective emotion. Also, other ER approaches, known to increase interoception—such as different forms of relaxation exercises, yoga, breathing patterns, or mindfulness courses—could then be evaluated with respect to their beneficial influence. It also has to be mentioned that in general, more biofeedback studies need to be conducted to help unravel its influence on decision making. Are traders less susceptible to decision biases when they are provided with live biofeedback? Can live biofeedback help managers to maintain control of highly emotional situations? Do consumers behave less impulsive during online shopping when they are provided with live biofeedback? We believe that answering these questions can contribute to more sophisticated NeuroIS tools that support users in taking more advantageous decisions.

5.7.3. Conclusions

Taken as a whole, this study demonstrates the potential of biofeedback-based NeuroIS tools and the relevance of ER for information systems. Generally speaking, emotions are an integral part of our lives that guide many facets of human experience. Who would want to live without emotions? However, although emotions are essential for taking advantageous decisions, they can also get out of control. NeuroIS tools can help us to increase emotional awareness, to improve our ER capabilities, and, in consequence, to avoid disadvantageous decisions with undesired consequences. In this sense, this chapter can also be understood as a motivation for IS researchers to incorporate the concept of emotion regulation in information systems research. Affective processes have been found to play a vital role in human-computer interaction (Deng and Poole, 2010; Riedl et al., 2010, 2011). Therefore, we believe that it is important to also take into account the users' individual emotion regulation processes and capabilities.

Chapter 6.

Conclusions and Future Work

Emotional processing lies at the heart of economic decision making. In this thesis we employed psychophysiological measures in order to assess subjects' emotional processing during decision making. We find evidence for the influence of emotions and ER on decision making. Furthermore, a NeuroIS live biofeedback tool was invented in order to improve subjects' emotional awareness.

This chapter is tripartite: First, the main contributions of the work at hand are highlighted. Second, limitations of the work as a whole and specifically with respect to the fields psychophysiology and ER are discussed. Finally, implications are drawn and relevant and interesting fields for future work are pointed out.

6.1. Contributions

In this section the contributions of the work at hand are listed. It is therefore ranged back to the introductory research questions. The results are especially relevant for researchers from IS and economics, who deal with the influence of emotions and ER on decision behavior.

> **Research Question 1:** *Do bidders in FPSB auctions experience regret, and if so, does regret influence bidders' decision making?*

Indeed, in Chapter 2 we provide evidence for physiological responses to informational feedback information, which can arguably be attributed to the emotion regret. This so called WR and LR feedback information is also reflected in subjects' average bids. Moreover, psychophysiological data indicates that the original assumption about the degree to which the bidders incorporate regret into their bids needs to be reviewed and possibly renewed. Three major findings can be taken away concerning an individual's emotion of regret in a FPSB auction: First, LR is more intense than WR, as it results in overall stronger skin conductance responses. Second, LR as measured by skin conductance is especially strong for high monetary levels of "missed opportunity." Third, there is no such pattern for WR. Instead the results point towards the finding that relief or rejoice are experienced for bids, which are close to an optimal bid. Summing up, these results support the notion that emotional decision processes can be deliberately manipulated by IS design.

> **Research Question 2:** *Do "joy of winning" and "frustration of losing" in FPSB auctions occur, and if so, which one is more prevalent?*

In Chapter 3 we find physiological evidence for both joy of winning and frustration of losing. As expected, losing is reflected in a more pronounced drop in HR than winning an auction—indicating that losing is afflicted with a lower valence (i.e. negative valence). Independent of the drawn valuation, winning induces stronger skin conductance responses, i.e. is experienced with a greater intensity than losing, (partly) contradicting the assumption that the aversion to losses is prevalent in FPSB auctions (cf. Goeree and Offerman, 2003). Interestingly, the more money is at stake the stronger the resulting emotional intensity. To some extent, this contradicts the notion that the experience of winning or losing an auction is largely independent of the money at stake (cf. van den Bos et al., 2008).

> **Research Question 3:** *What is the impact of incidental social images in FPSB auctions on emotions, emotion regulation and decision making?*

Internet shopping platforms often use affective images as design elements of their websites. Chapter 4 explores the effect of such images on the users' affective processes and behavior, again, in the context of FPSB auctions. In this laboratory experiment participants are either shown community images, competition images, or no images before they can place a bid. At first, we can confirm that the treatment manipulation is successful: Even though the images are completely unrelated to the task, participants' skin conductance responses in the treatment groups are significantly stronger compared to those in the control group. Moreover, competition images induce a stronger drop in participants'

HR than community images, indicating that competition images are perceived as less pleasant. However, the image influence seems to be unconscious in nature, as the participants state that the images neither affected their emotional state nor their bidding behavior. With respect to behavior, our first main result is that bidders systematically place lower bids in response to seeing competition images than they do in response to seeing community images. Furthermore, the effect on bidding behavior is partially mediated by subjects' affective processes in response to the images, as measured by HR. Moreover, results from skin conductance reveal that participants who use suppression as an ER strategy experience stronger emotional reactions in response to the images. Furthermore, the more participants aim at suppressing their emotions, the more they struggle to mitigate the influence of images on their bidding behavior. Whereas bids of participants with a low suppression score seem to be unaffected by the affective images, participants with a medium or high suppression score are found to be affected significantly. To the contrary, applying reappraisal as an ER strategy does not moderate the influence of affective images on bids and has only a marginal influence on bids overall. It does, however, has a mitigating influence on the intensity of the experienced emotions in response to seeing community images. Summing up, it becomes clear that even incidental images on electronic platforms are capable of unconsciously influencing emotional processing and shifting decision behavior systematically. The magnitude of this shift is moderated by subjects' suppression tendencies.

> **Design Objective:** *Development of a NeuroIS tool which increases subjects' awareness for their emotional state and rewards emotion regulation capablities.*

From the assumption that high awareness to the own emotional state and improved ER capabilities can contribute to improved financial decision making, in Chapter 5 a biofeedback based NeuroIS tool is designed, implemented, and evaluated which aims to support decision makers by rewarding successful ER—the Auction Game. To the best of our knowledge, this is the first serious game in which online biofeedback is directly applied to a financial decision making context. In addition to the *Rationalizer* by Philips and ABN AMRO, which displays biofeedback by means of a light bowl next to the monitor, this design artifact integrates biofeedback into the decision scenario and thereby aims at rewarding the users' ER capabilities. A core feature of this approach is that game difficulty is directly linked to the user's current emotional state. The emotional state is assessed by means of unobtrusive ECG measurements. Depending on the player's ability to down-regulate levels of high emotional arousal, the financial decision scenario of the game continuously adjusts itself and thereby becomes more (or less) difficult. The results of two conducted evaluation studies show that the game, as an one-time intervention in fact induces arousal and rewards down-regulation of arousal. Moreover, it provides an environment in which poor ER strategies are punished. In addition to that, it is found that biofeedback displayed in the Auction Game is meaningful for the users in the sense that it helps them to down regulate arousal and perform better in the game, as measured by decision performance.

6.2. Limitations of the Present Work

This work is self-evidently limited as it only investigates individuals' emotional and behavioral responses to previous affective or informative stimuli in an artificial setting such as the FPSB auction or the developed game. The generalizability of the presented findings with respect to other economic contexts or even to other auction formats is not necessarily given (cf. Adam et al., 2012). Hypotheses were derived by extensive investigation of previous literature and application of the emotional bidding framework by Adam et al. (2011). While the thesis as a whole certainly provides strong arguments for the influence of integral and incidental emotions and ER on human individuals' decision making, it does not provide an overall integrating framework which incorporates all findings generally. One reason for this is the novelty of both the topics psychophysiology and ER in economics and IS. Hence, further research is needed to synergize those promising fields. Additionally, this work solely employs the methodology of experimental economics enriched by psychophysiology in the aim to understand the influence of emotional constructs on decision making. See Falk and Heckman (2009) for a discussion of the methodology of experimental economics. The previous chapters have already discussed the limitations of the respective studies, see Sections 2.5.2, 3.5.1, 4.5.3 and 5.7.2. In the following paragraphs the discussion will be particularly set on the two domains psychophysiology and ER, as they are only little established so far in the domain of economics and IS.

6.2.1. Psychophysiology

The incorporation of psychophysiological measures into the field of experimental economics and IS has been subject to criticism and is widely debated (cf. Camerer et al., 2005). The following sections will tackle some occuring issues.

Assessability of Emotions Neurophysiology has been criticized for "providing little more than a picture of where things happen in the brain or, more cynically, as simply showing that behavior is caused in the nervous system (which never was in doubt)" (Camerer et al., 2005, p. 14). While this criticism is aimed at neuroimaging procedures especially the second part of this statement can equally be referred to psychophysiological indicators. In fact, skin conductance and cardiovascular activity are innervated by the autonomic nervous system (ANS), consisting of the systems parasympathetic and sympathetic nervous system; electrodermal activity can be employed for the measurement of a number of sympathetically innervated processes such as: activation, attention, significance or affective intensity of a stimulus (Dawson et al., 2007). Indeed, for psychophysiology multiple emotions can result in similar responses, when only one indicator is examined. For instance the anticipation of an oral exam and the anticipation of a reunion with an old friend after a couple of years may result in very similar emotional responses with respect to fear, when approximated with skin conductance.

However, whether the activity of the ANS is emotion-specific has been debated for more than a century (Ekman et al., 1983) and by now, evidence yields the notion that varying emotional states are reflected in associated psychophysiological indicators (Ekman et al., 1983; Collet et al., 1997; Kreibig, 2010). Without entering the discussion about the existence of basic emotions (Ekman, 1992), psychophysiology with its indicators (phasic) heart rate and skin conductance response (as measures for (para-)sympathetic activity) appears capable to adequately reflect an individual's positive and negative emotional response. Both measures are well established for stimulus intensity and valence, which are according to many psychologists the two major dimensions regarding emotional processing (Bradley, 2000). It is essential though, to accompany these measures by questionnaires or self-reports and a rigorous restricting experimental design which allows to isolate the emotional response (Adam et al., 2011).

Unifying Measures Many measures whirr around when it comes to studies employing electrodermal or cardiovascular activity, and there is extensive literature on psychophysiology in the social and physical sciences (cf. Bradley, 2000). It is highly important to determine ex ante, which measures should be assessed in order to limit the experimental effort and also to be capable to answer the respective research questions.

For instance, the drop in heart rate as well as the phasic bursts in skin conductance activity are sufficient indicators for the measurement of the intensity and valence of a discrete stimulus (e.g. Adam and Kroll, 2012; Astor et al., 2013). However, these measures do not aid our understanding of an individual's overall arousal state. Typical measures concerning the arousal level are overall heart rate, relative to the individual's baseline, as employed in Chapter 5 or the (tonic) skin conductance level. This work employed the assessment of phasic responses for skin conductance (SCR.amp) in Chapter 2, 3 and 4 and heart rate drop (i.e. ΔHR) in Chapter 3 and 4 subsequent to affective stimuli. In Chapter 5 we employed overall heart rate (i.e. ΘHR) as a proxy for (tonic) arousal. Also, one could have taken into account the heart rate variability (HRV) as a measure, which is also known to be a reliable index for parasympathetic processing and ER (Appelhans and Luecken, 2006; Fenton-O'Creevy et al., 2012).

Particularly skin conductance is vulnerable to measurement artifacts or errors (e.g. because of room temperature, body movement, previous usage of soap by participants or simply subjects being non-responders), which leads to a high measurement variability within and between the participants. While the measurement devices continuously improve, allowing to transmit psychophysiological indicators wirelessly, orderly experimental conditions are indispensable. If possible, a prescreening of participants can help to exclude non-responders, before starting the experiment. With respect to data treatment, normalization procedures of the signal against an appropriate baseline (such as an omnipresent external stimulus) are helpful as well as taking into account the sequence of the stimuli (as done in Chapter 3 and 4), as it can also reduce confounding factors such as stimulus novelty. Adam et al. (2011) provide a good methodological paper for assessing psychophysiological parameters in NeuroIS experiments. However, for future work it might be desirable to carry out a method paper which provides the experimenter with a toolbox in respect to the indicators of electrodermal and cardiovascular activity, depending on the research focus in economics and IS.

Neuroimaging versus Psychophysiology It is often mentioned that brain imaging techniques such as fMRI or PET, in contrast to psychophysiology are more detailed and precise as they can locate certain areas in the brain when emotions are processed (Camerer et al., 2005). In fact, neuroimaging studies provide a clear picture of which areas in the brain are activated during emotional processing. However, also the visualization of brain activation does not completely dissolve our understanding of its functioning due to its highly complex anatomical nature. In this context Taleb (2010) mentions that neuroscience often employs the size of the brain cortex as a proxy for intelligence. For instance, humans are succeeded by dolphins, these by apes. However, some birds—for instance parrots—are equally intelligent as dolphins, even though they have a much smaller cortex. In fact, for parrots the mentioned rule does not apply as for them intelligence correlates with different brain parts. This example shows that—also when working with neuroimaging tools—one has to be careful with too distant inferences. Apart from these comments, psychophysiological measures also offer certain advantages such as comparably low acquisition and operation costs (Dimoka et al., 2011), easy and unobtrusive assessment (allowing their usage in field studies), but also the acquisition of much larger data samples (Adam et al., 2011).

To sum it up, with respect to psychophysiological indicators, it is important to not make unrealistic demands in one's strive to add further insight into experimental economics. In line with Adam et al. (2011), it is important to mention that psychophysiology is no panacea. It always has to be accompanied by complementary questionnaires and a rigorous experimental design, assuring a high level of control. Also, researchers should always reconsider, whether the psychophysiological indicators can add significant value to the research question (Dimoka et al., 2012). Psychophysiological measures are no self purpose. The beauty of the discipline as such accrues from a clever treatment design with a dazzling idea, embedded in profound theory. By asking the right questions, psychophysiology should be considered the role of a judge, which helps the researcher to confirm or discard our theoretical assumptions.

6.2.2. Emotion Regulation

Hypothesis Building The concept of ER originally stems from developmental psychology and then flourished psychology, thereby cutting many traditional subdisciplinary boundaries within its domain (Gross, 1998b). Psychological literature often refers to emotion response tendencies, when subjects aim at modulating or regulating emotions (cf. Gross, 1998b). However, how these *tendencies* translate into decision behavior is to a large part not yet resolved. With respect to ER, hypothesis building in Chapter 4 and 5 varies to a certain extent. In Chapter 5 subjects are instructed to inhibit their emotions in order to decrease their arousal and therefore game difficulty. Both strategies, reappraisal and suppression, have been shown to successfully down-regulate positive emotional states and thereby lead to a decreased average heart rate (Gross and Levenson, 1997; Giuliani et al., 2008). As the game aims at being motivating and entertaining—eliciting positive emotional states—it particularly rewards the successful down-regulation of arousal and therefore the two ER strategies.

To the contrary, the study conducted in Chapter 4 makes use of spontaneous ER, i.e. subjects are not instructed in any respect about ER (cf. Volokhov and Demaree, 2010). Therefore their interaction with ER occurs rather habitually or even unconsciously. Previous studies have shown that suppression can have certain drawbacks in the respect that it fails to mitigate (aversive) emotions and can even result in increased sympathetic responses, such as strong skin conductance responses (Gross, 1998a).[1] Consequently we hypothesized that suppression may also result in more unpremedidated bids. We will refer to the general influence of ER on decision behavior in the next section.

We measured ER by German and English versions of the ERQ (Gross and John, 2003; Abler and Kessler, 2009), a validated measure for the two prevalent strategies of ER. Nevertheless, subjects' tendency to regulate emotions is also correlated with age, cultural background, gender, health related and other personality traits. It is always hard to draw causality from correlation. Potentially, future studies should also take into account further questionnaires, which also control for other constructs, related to ER, such as the Positive Negative Affect Scale (PANAS) (cf. Watson et al., 1988) or the Big Five (cf. McCrae and John, 1992).

[1]For down-regulation of positive emotions, the physiological indicator HR reacts similar in response to reappraisal and suppression (i.e. heart rate decelerates) (Gross and Levenson, 1997) while skin conductance differs for the two regulation strategies (i.e. skin conductance increases for suppression, while there are no overall consistent findings for reappraisal) (Gross, 1998a).

6.3. Implications and Future Work

This thesis provides evidence for an influence of emotions and ER on economic decision making in simplified electronic markets. Implications of the individual chapters can be found in the Sections 2.5.1, 4.5.1, 4.5.2 and 5.7.1. Here the consideration is limited to general implications of this thesis and possible directions for future work.

Using NeuroIS to Enhance Theory in Economics and IS The experiments carried out in this thesis provide physiological evidence for the integral emotions regret, joy and frustration in subjects' decision processes in electronic auctions; but also for constructs such as social presence or competition. In line with previous research we confirm that psychophysiological indicators such as cardiovascular activity and skin conductance can reliably measure emotional bursts during economic decision making (cf. Smith and Dickhaut, 2005; van't Wout et al., 2006). Psychophysiology contributes significantly to economists' and information scientists' strive to step from previously more or less arbitrary assumptions, with respect to subjects' emotionality during decision making, towards a clear testability of hypotheses. It also enhances our understanding and conception of theoretical constructs regarding how different facets of IS are emotionally processed by the recipient and how they ultimately stimulate behavior on electronic platforms. Future research on IS constructs such as the Technology Acceptance Model (TAM) or facets of Human Computer Interaction (HCI), with its usability metrics such as perceived usefulness or affective information processing, should also be supplemented by psychophysiology (cf. Koller and Walla, 2012). This could for instance inform research on website design about how these constructs are emotionally (i.e. in terms of valence and intensity) experienced.

Employment of Unconscious Processes As shown in this thesis psychophysiological measures allow us to assess hidden emotional processes, which would have been non-assessable otherwise. Taking into account the questionnaire data, it was found that this process can be beyond conscious awareness. It is also recognized that affective reactions, measured by subjects' drop in heart rate, can be employed—to a certain extent—as a mediator for subjects' behavior.

As described by Dimoka et al. (2011, p. 6), tools from neurophysiology can capture unconscious or automatic processes opposed to self-assessments since "subjects might not be able or willing to express them verbally or behaviorally." Due to automated processing or social desirability subjects sometimes "cannot" or "do not want to" give correct answers in surveys (Koller and Walla, 2012). These otherwise immeasurable processes can be captured by neurophysiology to some extent. Thus, in order to study the impact of concepts from IS or economics it is important to note that an application of tools from neurophysiology can complementarily assess the users' hidden affective processes. The investigation of unconscious aspects of constructs of economics and IS should gain further consideration, as neurophysiology provides useful and unobtrusive tools to assess these.

Automated emotional processes may be an important cornerstone for many decision patterns and biases in economics, which are not completely resolved yet, such as the disposition effect, loss aversion or the house-money effect[2]. Also extensively researched constructs in IS such as TAM with its concepts perceived usefulness or ease-of-use could be extended by tools from neurophysiology (Dimoka et al., 2011). Arising questions related to the usability or adoption of electronic markets might profit from further insights about the influence of unconscious affective information processing (Koller and Walla, 2012).

Enhancing our Understanding of Emotion Regulation Opposed to emotions, the concept of ER has not gained extensive attention in the field of IS and economics so far. However, Chapters 4 and 5 provide evidence that controlling for ER on decision making considerably helps to explain human decision behavior. Chapter 4 provides evidence that using suppression increases one's affection to the emotional image stimuli—and also results in a stronger bidding bias. In the game developed in Chapter 5 arousal is directly connected to game difficulty. With respect to whether ER strategies—or even which ER strategy—should be applied in order to make profitable decisions, we cannot conclude that inhibiting ones emotions is generally for the better or for worse. The effects of ER on decision making may be highly context-dependent. Further research is needed in order to develop frameworks and models about the

[2]The house-money effect commonly describes the observation that prior windfall gains lead to increased risk seeking (Thaler and Johnson, 1990).

coherence of emotions, their regulation, and (market) decision making. Also the emotional bidding framework by Adam et al. (2011) should be enhanced as it, so far, does not account for the influencing role of ER. In order to better understand the connection of ER and decision making, future research should decisively manipulate subjects' ER strategies before or during the decision making task (cf. Sokol-Hessner et al., 2008). Breathing patterns, mindfulness courses or yoga excercises, frequently linked to improved ER (Arch and Craske, 2006), could also help to disentangle more rigorously the connection of ER strategies with subjects' information retrieval.

As mentioned, both the physiological and economic effects of the respective ER strategies are not yet completely resolved and may depend on a multitude of factors. Therefore, it is highly interesting for future research. Factors such as whether ER is incidental or instructed and whether the task at hand deals with ambiguity or uncertainty may have a significant influence (cf. Heilman et al., 2010). Also whether, for instance, the economic task itself induces positive or negative emotions, or whether it is cognitively demanding, may significantly alter the effectiveness of whether ER strategies can be successfully employed or not. Finally, field study examinations with decision makers under high levels of stress, such as stock market traders or investors, may complement experimental findings, since ER in the real world adds the necessary external validity (cf. Fenton-O'Creevy et al., 2011).

Adaptive NeuroIS in Electronic Markets Applying sophisticated algorithms and multi-modal arousal parameters will allow one to unobtrusively gain information about the user's emotional state in realtime. These multi-modal parameters could also include unobtrusive measures such as pupil dilation (Bradley et al., 2008) or even indicators apart from psychophysiology, for instance tools assessing mouse pressure (e.g. Schaaff et al., 2012). Heart rate, meanwhile can be assessed fast, reliably and also wirelessly, assuring a high validity through an unobtrusive measurement—allowing to carry the method for instance into the trading floor, measuring the traders' emotional state on site without constraints (cf. Lo and Repin, 2002). Psychophysiology, as opposed to brain imaging tools, allows a continuous and simultaneous assessment of many human market participants. Moreover, psychophysiological tools can easily be used in the field. This might be of interest for (i) the market participant, (ii) the market platform provider and (iii) even the regulator. First, from a market participant's perception one could think of NeuroIS tools which act for decision support during the user's interaction with the platform. Depending on the user's emotional state the displayed information complexity could then be increased or narrowed, in order to adapt the decision scenario to the user. Also the system could then aid the user and prevent him or her against rash impulsive decisions which might be regretted afterwards. Second, from a platform provider's viewpoint, who engineers the market, participants' sentiment within a market could be assessed. Measures such as the mean or the volatility of arousal in the market could provide information about participants' emotional states in the market; and whether these converge or diverge. Platform providers could then analyze which distribution of arousal might be optimal for profit in an auction market; or for instance for liquidity in two-sided electronic markets. Third, market regulators could—depending on this arousal distribution—dynamically decide to change certain market elements, such as increasing or reducing the number of algorithmic traders in the markets, or change the set of rules in the market (e.g. Zhang et al., 2012). Future research could, on the one hand, examine how these adaptive systems improve an user's actual decision making and, on the other hand, whether such adaptive design helps to strengthen markets in order to become more robust against market price bubbles, herding behavior or panic during economic downturns.

Biofeedback and Decision Making Psychophysiological indicators can also be unobtrusively employed for live biofeedback. Arousal parameters, employing physiological derivatives such as heart rate, heart rate variability, eye-tracking or skin conductance promise fast assessment, processing and are capable to provide instantaneous visual or auditive feedback (cf. Ouwerkerk, 2011).

The developed NeuroIS application (cf. Chapter 5) provides the insight that the indication of an arousal bar can provide useful information for the user about his or her emotional state on an IS platform, potentially even increasing emotional awareness. In fact, the resulting biofeedback could be usefully employed by participants in the game. However, to what extent biofeedback can actually support retrieval of information, help to down-regulate arousal and support decision making in general is still an open question which deserves more research in future.

The influence of biofeedback on cognition and decision making is still vividly discussed (cf. Wang et al., 2010; Djajadiningrat et al., 2009). Gimpel et al. (2013) provide a good overview in what respect biofeedback might be useful: monitoring/recording, live feedback, warning/intervention and training. More research is needed to figure out to what extent biofeedback can actually help to warn the user in dealing with stressful decision scenarios or when he or she falls prey to decision biases. Significant findings in the laboratory could then be validated externally with stock market traders or other professionals, working in exhausting jobs. However, as Vom Brocke et al. (2013, p.2) put it "the consideration of neuroscience is still in its infancy in IS design science research." Ultimately, research on this topic could result in a decision support system which identifies highly emotional states such as auction fever and warns the user, so that a previously non-conscious decision bias is detected and becomes a conscious deliberate choice—which ultimately beneficially influences decision making.

Part I.

Appendix

Appendix A.

Participant Instructions and Comprehension Questions

A.1. Participant Instructions for Study on Regret

Appendix A.1 lists the participants instructions of the studies presented in Chapter 2 and Chapter 3. The material was translated to English from the original German version. Please note that the instructions are only translations for information; they are not intended to be used in the lab. The instructions in the original language were carefully polished in grammar, style, comprehensibility, and avoidance of strategic guidance.

A.1.1. Instructions

You are participating in an experiment in which your decision-making behavior in auctions is examined. During the experiment your skin conductance, your pulse and your heart rate will be recorded and analyzed in a subsequent analysis. You can earn money in this experiment. How much you earn depends on your decisions. These instructions explain how to decide in order to earn money. The amount of money earned during the experiment will be paid out in cash after the experiment. Please read the following paragraphs carefully.

Description of the Experiment After having read these instructions you will be asked some comprehension questions about the auction mechanism. The comprehension questions are followed by a 5-minute rest period. This rest period is required for the calibration and analysis of the physiological data. Please keep calm during this rest period, avoid movements and relax. The auction begins with three practice rounds. In these practice rounds you have the opportunity to practice the auction without any consequences for your actual cash balance. The subsequent main part of the experiment consists of **50 auctions**. Structure and course of these auction sequences are described below. At the end of the main part you will be asked to enter your identification number in a predefined box on the screen. The data recorded in the questionnaires and the auctions are processed anonymously using your identification number. Only this identification number links you to the collected data in the experiment. Each participant makes his or her decisions in isolation from the other participants at a computer terminal. Communication between participants is not allowed. We kindly ask you to use the computer only to enter your decisions and to answer the questions displayed on the screen. Please do not start or stop any programs or change any settings.

Description of an Auction Two computerized agents take part in each of the 50 auctions. The agents were programmed so that they maximize their expected profits, when participating in an auction with two identically programmed computers. In each auction one single fictive good is auctioned off. At the beginning of each auction round, each bidder is assigned with a private valuation. This private valuation indicates how much the fictive good is worth for you. The selling of the goods is carried out by a first-price auction. In this auction each bidder places one irreversible bid, without knowing the bids of other bidders. With your bid, you specify how much you are willing to pay for the fictive good. Once all bids are submitted, the experimental software automatically determines the highest bid. The bidder with the highest bid wins the auction and has to pay the price of its bid.

If you win an auction, the difference between your valuation and the auction price will be credited to your account. An example: your valuation is 60 and you win the auction for the price of 45, then you will be credited 60 - 45 = 15 monetary units. In case you and one of the computerized bidders place the highest bid with the same amount, you are automatically identified as the highest bidder. If you win an auction and your bid is higher than your valuation, you will suffer financial losses. An example: your valuation is 60 and you win the auction for the price of 70, then you lose 60 - 70 = -10 monetary units. If you lose an auction, your payment for this auction is equal to 0.

The Auction Process

1. **Receiving your valuation** At the start of each auction your valuation will appear on the computer screen. Your valuation will randomly take on values of 50, 60, 70, 80, and 90. You will receive every valuation for 10 times in a row. The valuations for the two computerized bidding agents are randomly drawn from the distribution of 0-100 prior to each auction. Note: the valuations of the bidding agents are drawn independently in each auction, your valuation, however, remains the same over subsequent 10 rounds. The bidding agents follow a fixed bidding strategy, which is not affected by your bidding decisions.

2. **Placing your bid** Next, a keypad will appear on screen to enter your bid. The keypad is unlocked after 5 seconds. Consider your bid first and then click on the box which displays your favored bidding amount when the keypad is unlocked. In

the upper right corner of the screen you will see a box with a reminder of your own valuation. Once you selected a bidding amount on the keypad with a mouse click, your bid is accepted and it will appear in the upper right box. The bidding agents place their bids before you. Just like you do not know their bids, your bidding amount is not known to them.

3. **Determination of the auction price** Once all bids have been submitted, the experimental software automatically determines the winner and the price of the good. The bidder with the highest bid wins the auction and pays the price of his own bid. The winner earns the difference between his valuation and the highest value bid. The other two bidders have not won the auction and receive 0. *Let's say your valuation is 80 and you enter a bid of 65 and your computerized bidders have placed bids at 47 and 51. In this case your bid is higher than the other two bids. You win the auction and receive a payoff of 80-65 = 15. The two computerized agents receive 0. Suppose the bids of the computerized bidder would be 47 and 66. In this case the bidder with the bid 66 wins the auction. Your profit in this case is 0.*

4. **Viewing the auction result** After completion of the pricing you will receive the following information:
   - Whether you have won or lost the just completed auction.
   - Your "money left on the table": This value is 0 if you do not win the auction. If you win the auction, it is calculated as the value of your bid minus the second highest bid (winner regret condition).[1][2]
   - The second highest bid (winner regret condition).[3][4]

5. **Start of a new auction**

Payoff You have an experimental account. This account accumulates your profits and losses over a total of 50 auctions. Your account closing balance will be paid out

[1] In the loser regret condition the following information will be given instead; Your "missed opportunity to win": This value is always 0 if you win the auction or if your valuation is lower than the highest bid. In all other cases it will be calculated by subtracting the highest bid from your valuation.

[2] None of these information will be given to the participant in the no regret condition.

[3] None of these information will be given to the participant in the no regret condition.

[4] In the loser regret condition the following information will be given instead: The highest bid.

in cash after the experiment. In this experiment, monetary units (MU) are used. 1 MU in the experiment corresponds to a payoff of EURO cents 3. At the beginning of the experiment, you will receive an initial endowment of 100 MU (€ 3), which will be credited to your experimental account.

...a few notes at the end If you have questions about the experiment, please remain seated quietly and give the experimenter a signal by raising your hand. Please wait until the experimenter is at your seat and pose your question as quietly as possible.

To interact with the experimental system, please use your free hand. The hand that is connected to the measuring technique must be kept quiet during the entire experiment. Try to avoid any movement, as this may distort the results of the measurements. At the end of the experiment stay at your seat and wait until the experiment has removed the measuring electrodes from your skin. These instructions should be left on your seat.

Important note: Please make sure that you use your mouse during the experiment as quietly as possible, try to apply very little power when clicking on the mouse. You will now receive ear muffs to reduce the influence of noise on the measures.

In the remainder we attach a set of questions which the participants had to answer correctly before the actual experiment proceeded. Each time the participant picked an incorrect answer option the following message occurred: "This answer is not correct! Please have a look at the instruction material for further information". Subsequently the participant could answer the question again. The correct answers are italicized. After the participant had answered all questions correctly, the following message was displayed on the screen: "Now a 5-minute calibration period starts, which is necessary, to calibrate the physiological measuring instruments. Please try to relax and focus on the cross in the middle of the screen."

A.2. Participant Instructions for the Emotion Induction Study

Appendix A.2 lists the participants instructions of the studies presented in Chapter 4. The material was translated to English from the original German version. Please note that the instructions are only translations for information; they are not intended to be used in the lab. The instructions in the original language were carefully polished in grammar, style, comprehensibility, and avoidance of strategic guidance. The bidding screen and also the bidding fields in detail were also depicted in the instructions (in illustrated in Figure A.2 and Figure A.1.

A.2.1. Instructions

You are participating in an experiment in which your decision-making behavior in auctions is examined. During the experiment your skin conductance, your pulse and your heart rate will be recorded and analyzed in a subsequent analysis. You can earn money in this experiment. How much you earn depends on your decisions. These instructions explain how to decide in order to earn money. The amount of money earned during the experiment will be paid out in cash after the experiment. Therefore it is necessary to read the following paragraphs carefully.

Course of the Experiment Subsequently to this instruction phase some comprehension questions regarding the procedure of the auction will be asked. A 5-minute rest period will follow. The rest period is required for the calibration and analysis of the physiological data. Please keep calm during this rest period, avoid movements and relax. The main part of the experiment will last altogether about 45 minutes. Structure and course of these auction sequences are described below. Subsequent to the experiment it is asked to fill out a participant questionnaire. The data recorded in the questionnaires and the auctions are processed anonymously using your identification number. A mapping between you and the experimental data collected during the experiment is only possible via your personal participant code, which is only in your possession. Each participant makes his or her decisions isolated from the other participants at a computer terminal. Communication between participants is not allowed. We ask you to use the computer only to enter your decisions and to answer the questions displayed on the screen. Please do not start or stop any programs or change any settings.

Description of an Auction In each auction you and two computerized agents take part. The agents were programmed to maximize their expected profits, when participating in an auction with two identically programmed computers. In each auction one single fictive good is auctioned off. At the beginning of each auction, each bidder is assigned with a private valuation for the good. This valuation indicates how much the fictive good is worth to you. The auction of the goods is carried out by a first-price auction. This means the bidder who places the highest bid receives the good and has to pay precisely the price of his or her placed bid. Hence, each bidder places one irreversible bid, without knowing any of the opponent bids. With your bid, you specify how much you are willing to pay for the good. Once all bids are submitted, the experimental software automatically determines the highest bid. The bidder with the highest bid wins the auction and has to pay the price of his or her bid. This bidder's profit is then the received valuation minus the price that the bidder placed with his or her bid. Only after completion of all played auctions the final results will be displayed.

If you win an auction, the difference between your valuation and the auction price will be credited to your experimental account. *Example: your valuation is 70 and you win the auction for the price of 45, then you will be credited 70 - 45 = 25 monetary units.*
In case you and one of the computerized bidders place the highest bid with the same amount, you are automatically identified as the highest bidder.
If you win an auction and your bid is higher than your valuation, you will suffer financial losses. *Example: your valuation is 60 and you win the auction for the price of 70, then you lose 60 - 70 = -10 monetary units*
If you lose an auction, your payment for this auction is equal to 0. *Example: your valuation is 65 and you lose the auction with a bid of 33. One of the computerized bidders has placed a higher bid. In this case your payment is 0 monetary units.*

Course of the auctions

1. **Multimedia display** At the beginning of each auction round a multimedia overlay is indicated. Let this overlay appeal to you.[5]

2. **Valuation Information and Bid Placement** In the next step your valuation on the screen will be displayed on the screen. Your valuation will take on values of 60, 65, 70, 75 and 80 in random order. Additionally, an 80-fields appears on the bidding screen. Each field is labeled with a number in order, which stands for a possible bid. With a click on the bidding field you place a bid for the good at the amount of the respective number. Please note: you have only 10 seconds time to place a bid.

   On the next page you will see an example screen.

   In order to simplify the submission of the bid, a black bar appears in each bidding field. It is a graphical indicator for your winning probability. It indicates the probability to win the auction with the respective bid. If the black bar does not cover the field at all, your winning probability is 0%. If the field is completely covered your winning probablity is 100%.

   Example: Consider again the picture above. You see on the top left, that your valuation is 60. Now, consider the picture on the next page. You see here a depicted bidding field. By clicking on this bidding field you place a bid in the amount of 47. Respectively the black bar stands for the winning probability, in this case a little less than 50%. In case you win the auction, you receive a payment of 60 - 47 = 13 monetary units. In case you lose the auction, you receive 0 monetary units.

   Please note again, that the time for you decision is restricted to 10 seconds. The countdown for your remaining time is indicated on the top right of the screen. In case you do not come to a decision within these 10 seconds and do not place a bid, you cannot realize any profit.

   Strategy of Computer Agents As mentioned earlier, you bid against 2 computerized agents. The valuations for the two bidding agents are drawn previously to each auction randomly from a unity distribution of 0-100. Imagine an urn with 101

[5] This first item was omitted in the NO condition, where no images were shown at all.

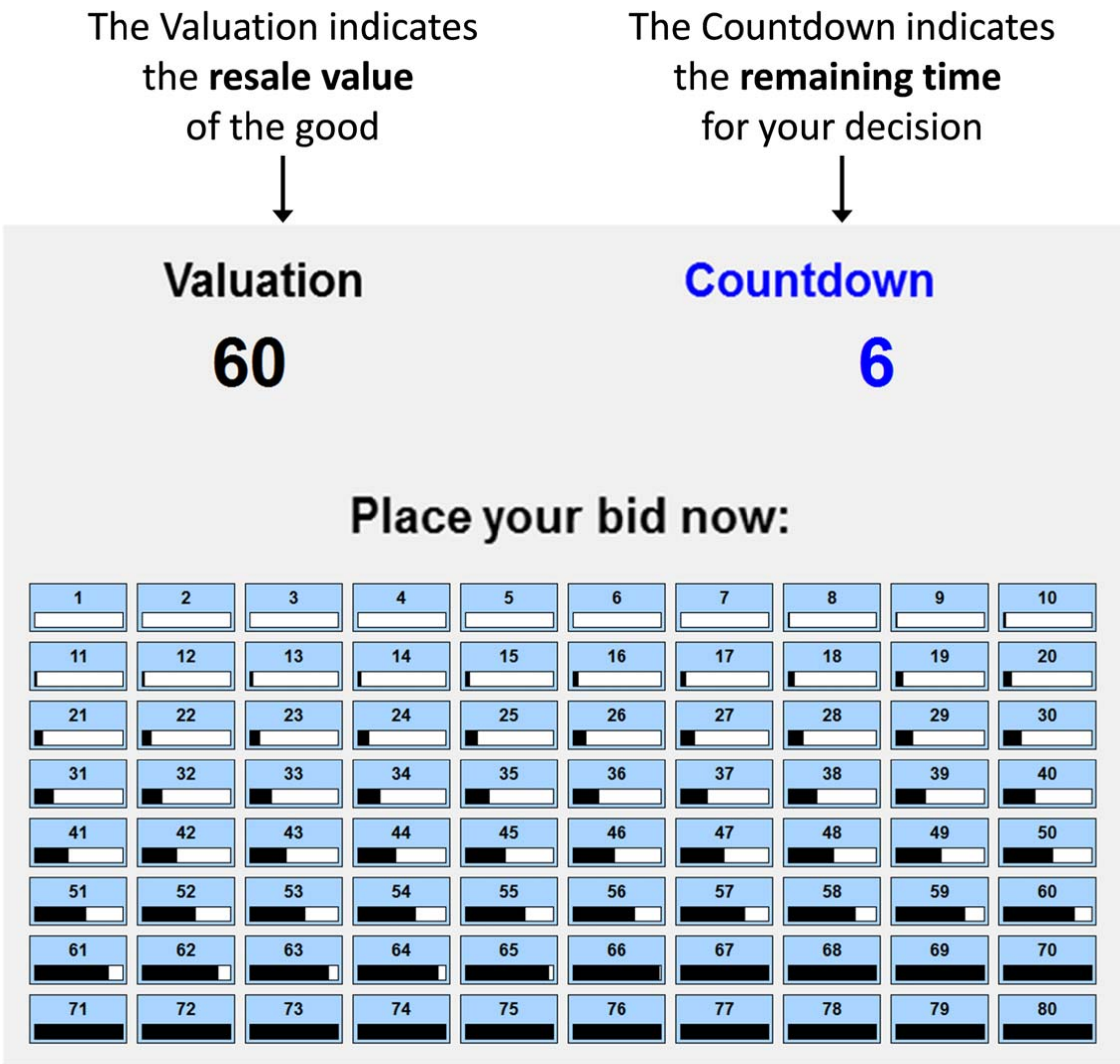


Figure A.1.: Bidding Screen for Participants

balls. Each ball is labeled with a number, the first with 0, the second with 1, the third with 2 and so on. The last ball is labeled with the number 100. Now, you pull a ball from the urn. Each ball corresponds to a possible valuation which your computerized opponents receive. Notice: The valuation for each bidding agent is drawn in each auction independently from this distribution. The bids, which the computers subsequently place, follow a determined bidding strategy, which is not influenced by your bidding decisions. The bidding agents place their bids before you. Same as you do not know the bids of the bidding agents, also the bidding agents do not know your bid.

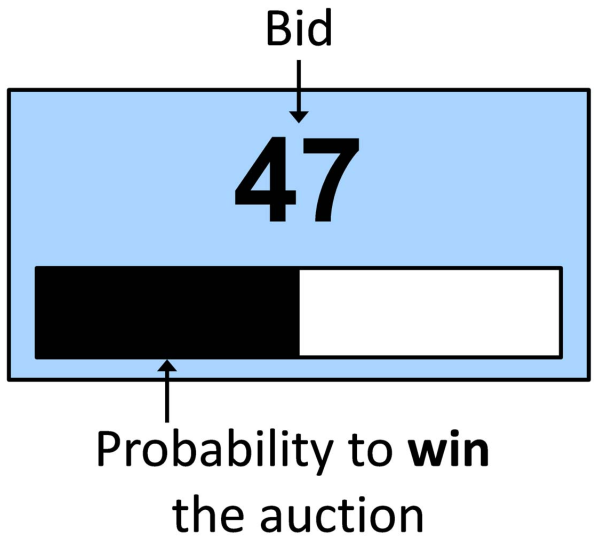


Figure A.2.: Bidding Field

3. **Price Determination** Once all bids have been submitted, the experimental software automatically determines the winner and the price of the good. The bidder with the highest bid wins the auction and pays the price of the placed bid. The winner earns the difference between his or her valuation and the highest bid. The other two bidders, who did not win the auction, receive a payment of 0.

   Attached some examples for the price determination:

   Example: Let us assume, your valuation is 80 and you place a bid of 65 and your computerized opponents placed 39 and 22. In this case your bid is higher than those of your two opponents. You win the auction and receive a payment of 80 - 65 = 15 monetary units. The two computerized agents receive a payment of 0.

   Example: Assume the bids of the computerized bidders are 47 and 66. In this case the bidder placing a bid of 66 wins the auction. Your payment in that case is 0.

4. **Auction Result** As mentioned before, you do not receive any information regarding your results at the end of the individual auctions. Only after the final end of all auctions you receive a list of all your played auctions and your amount won. Thereby your valuations, your bids, the bid of the computerized agents and your respective gains is presented.

Payoff You have an experimental account. This account accumulates your gains and losses over the participated auctions. Your final account balance will be paid out in cash after the experiment. In this experiment, monetary units (MU) are used. 1 MU in the experiment corresponds to a payoff of 4 Eurocents (€ 0.04). At the beginning of the experiment, you will receive an initial endowment of 100 MU (€ 4.00, which will be credited to your experimental account.

... a few notes at the end If you have questions about the experiment, please remain seated quietly and give the experimenter a signal by raising your hand. Please wait until the experimenter is at your seat and ask your question as quietly as possible. To interact with the experimental system, please use your free hand. The hand that is connected to the measuring technique must be kept quiet during the entire experiment. Try to avoid any movement, as this may distort the results of the measurements. At the end of the experiment stay at your seat and wait until the experiment has removed the measuring electrodes from your skin. These instructions should be left on your seat.

Important note: Please make sure that you use your mouse during the experiment as quietly as possible, try to apply very little power when clicking on the mouse. You will now receive ear muffs to reduce the influence of noise on the measures

In the remainder we attached a set of questions which the participants had to answer correctly before the actual experiment proceeded. Each time the participant picked an incorrect answer option the following message occurred: "This answer is not correct! Please have a look at the instruction material for further information". Subsequently the participant could answer the question again. The correct answers are italicized. After the participant had answered all questions correctly, the following message was displayed on the screen: "Now a 5-minute calibration period starts, which is necessary, to calibrate the physiological measuring instruments. Please try to relax and focus on the cross in the middle of the screen."

A.3. Participant Instructions for the Auction Game

Appendix A.3 lists the participants instructions of Evaluation Study I presented in Chapter 5. The material was translated to English from the original German version.[6] Please note that the instructions are only translations for information; they are not intended to be used in the lab. The instructions in the original language were carefully polished in grammar, style, comprehensibility. The paper instructions for Evaluation Study II were shorter as more information of the game mechanics was shifted to the subsequent game tutorial. At entrance, participants received information on how to tighten the chest belt of the EKG move and how to apply it. Furthermore, subjects received information regarding anonymity of the retrieved data and the subsequent payment. The starting screen is depicted in Figure A.3 and the game screen with annotations in Figure A.4.

A.3.1. Instructions

In the following the "Auction Game" will be introduced. Please read through the complete instructions before starting the game.

Goal of the game The "Auction Game" is a trading simulation where you can sell or buy a virtual good for an offered price. Depending on your decisions you will earn or lose money. The goal of the game is to earn as much money as possible. As soon as you reach a certain level of wealth you will be forwarded to the next level.

Start of the game Before beginning to play the game please start the Tutorial to receive a brief practical introduction to the basics of the game play. Afterwards please inform the experimenter by raising your hand thus he can enter all necessary information for you and enable you to start the game.

After entering all necessary parameters a **5-minute resting period** starts during which only a blue screen with a black cross appears on the screen. This resting period is crucial for the evaluation and calibration of the physiological data. Please stay calm during the resting period, avoid any movements and relax. Subsequent you will proceed to the first level of the game automatically. Prior to each level you will receive a short

[6]I thank Eike Holst for the translation of the material.

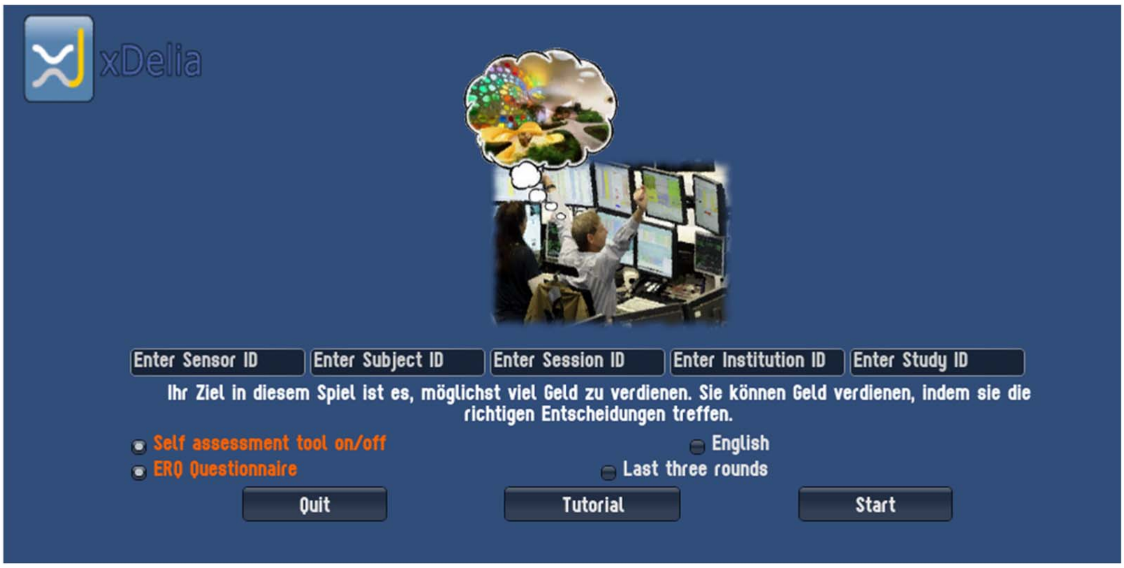


Figure A.3.: Start Screen.

overview of the current level displaying your initial wealth, the wealth to be reached and the new features of the current level. Finally you will proceed to the game screen.

The game screen The clock in the up left corner and the money pile in the low right corner display your progress in the current level. The money pile shows you how much money you already earned in the current level and how far you are away from reaching the goal of the level. The clock indicates the number of your current level and how much time is left to complete the level.
Three clouds will appear one after another somewhere on the screen as estimations of the true market price of the virtual good. Depending on the level additional clouds may appear which contain further numbers or information. Those clouds are distinguishable optically of the relevant clouds and contain wrong information.
In the low middle of the screen the decision buttons “buy”, “sell” and “no trade” are placed. Here also the offered price is displayed to which you can decide to buy or sell the good. The price is always the same for buying and selling. Alternatively you can choose “no trade” and skip a decision making round. These buttons only get active after all clouds appeared. When you made your decision, here the gain or loss that results from your decision will be displayed.

In the up right corner you can see the indication of your level of arousal on a scale between 1 (low) to 5 (high). The higher your level of arousal is, the higher is the level of difficulty of the game. That means that with a higher level of arousal it becomes more difficult to calculate the mean of the displayed estimation clouds. Additionally the color of the clouds represents your level of arousal.[7]

Figure A.4.: Game Screen

Course of the game You will try to realize gains by making several consecutive decisions whether to buy or to sell a virtual good and thus you will increase your wealth. You can make your decisions by clicking on of the buttons “Sell” or “Buy.” Alternatively you can skip the current decision by using the button “No trade.” First three or more clouds will appear in the game. Three of these clouds serve as indicators for the market price, all other clouds are only disturbing elements. The clouds appear on the screen one after another for a short moment and then disappear. Given a high level of arousal it is

[7]The above paragraph was omitted in the NBF treatment, as there is no biofeedback display in that group.

possible that the clouds are hardly visible so that you cannot recognize them properly. Subsequently you have to make your decision whether to buy or to sell within maximum 2 seconds. You make your decision basing on the information regarding the market price of the good that you received by the clouds that appeared. The true market price is the mean of the three sums which have been displayed in the clouds of identical shape. Afterwards you receive a short feedback regarding the correctness of your decision (and the sum you gained or lost respectively) and the next decision round begins. If you hesitate too long for making your decision a penalty of € 5 will reduce your wealth and the next decision round begins. The level is completed successfully when you reached the given level of wealth. After completing a level you are asked for a self-assessment of your arousal on a scale from 1 (low arousal) to 5 (high arousal). Please take note that you must complete each level within maximum 4 minutes. You realize a gain by utilizing the advantage of your offer. Given the market price is higher than the price that is offered to you, you realize a gain by buying the good. Anon selling the good would lead to a loss.

Example: The mean of the three relevant clouds is € 43 and you have an offer to buy or sell the good to a price of € 40. If you decide to buy the good you will utilize the advantage of the available offer, because you could buy the good to a price that is lower than the market price. You will realize a gain of € 43 - € 40 = € 3. If you decide to sell the good in this case you will sell it to a price that is lower than the market price and you will lose € 3.

The game ends as soon as one of the following situations occurs: 1. You are eliminated because you need more than 4 minutes to complete the level. 2. You are eliminated because your current wealth dropped to more than € 10 below the entry criteria of the level (this is not possible in the first level). 3. You completed level 7 successfully.

Please take note: The higher your level of arousal is, the higher is the level of difficulty of the game. This means: A high level of arousal increases the influence of distracting elements and effects on the game and it will get more difficult for you to calculate the mean of the clouds and thus to realize gains. These elements and effects vary from level to level and will be briefly explained prior to each level.

In the remainder subjects were walked through a tutorial of the game before they started playing.

A.4. Comprehension Questions

Comprehension Questions for studies presented in Chapter 2, Chapter 3 and Chapter 4. Before the experiment begins, please answer the following questions, which address the content of the instructions.

1. The winner of a First-Price Sealed-Bid Auction placed...
   a) *...the highest bid and pays the price of her/his bid.*
   b) ...the second highest bid and pays the price of her/his bid.
   c) ...the highest bid and pays the bid which the second highest bidder placed.

2. What is the relationship between your payoff and your valuation?
   a) The valuation is my payoff, when I win the auction.
   b) *The difference between my bid and my valuation determines my payoff, when I win the auction.*
   c) For the payoff only the price is of relevance.

3. How do your decisions influence the computerized bidders?
   a) They always place lower bids than I did in the previous round.
   b) They always place higher bids than I did in the previous round.
   c) *My decisions do not influence the bids of the computerized bidders.*

4. What is the opponent bidders' valuation?
   a) *It is drawn in each auction from a distribution ranging from 0 to 100.*
   b) It ranges between 50 and 90.
   c) It corresponds to my own valuation.

5. The "missed opportunity" indicates for the loser...[8]
   a) ...what the winner pays.
   b) *...the difference between her/his valuation and the highest bid, in case he lost the auction and has a valuation above the highest placed bid.*

[8] This item did not occur in the Winner Regret treatment of the study described in Chapter 2 and in the study described in Chapter 4.

   c) ...the expected profit.

6. The “money left on the table” indicates for the winner...[9]

   a) ...what the loser has to pay.

   b) *...the difference between her/his bid and the second highest bid.*

   c) ...the amount he won.

[9]This item did not occur in the Loser Regret treatment of the study described in Chapter 2 and in the study described in Chapter 4

Appendix B.

Supplementary Material

B.1. Supplementary Analyses for Chapter 3

It can also be argued that the individual SCR after receiving the respective result information—for various reasons—is a better baseline benchmark compared to the revelation of the results. Therefore we reevaluate the experimental data using this benchmark. Table B.1 contrasts SCR.amp to the auction outcome as dependent variable for two different baselines used for calculation: the left part shows SCR.amp for the baseline *average response to value information* (ref_value); and the right part shows SCR.amp to the baseline *average response to result information* (ref_result). Again we account for the fact of repeated measures for each subject by using robust standard errors clustered by subject. A comparison between the two regressions reveals that the results essentially remain unchanged for the two different baselines. Both independent variables (dummy_winner and value_class) remain significant. For the purpose of clarity we do only report the results for the chosen baseline measure ref_value in the paper.

Table B.2 represents a set of regression tables, which shows that the influence of the variables value_class and avg_nom_payoff is significant on SCR.amp and that this result holds for both baseline measures ref_value and ref_result. Since value_class and avg_nom_payoff are highly correlated (Pearson's $r = 0.799$, $p < .001$), we only use one variable at a time. Analogously to Table B.1 the two left columns use the baseline measures ref_value, the two right columns use ref_result. Both variables turn out to be significant for the regressions we carry out. For the purpose of clarity we report only the results for the chosen baseline measure ref_value in the main thesis.

Table B.1.: Regression Models for Different Baselines (Standard Errors Adjusted for 59 Clusters in Subject)

	Dependent variables							
	SCR.amp (ref_value)				**SCR.amp (ref_result)**			
Independent variables	**B**	**SE**	***t*-Stat**	***p*-val**	**B**	**SE**	***t*-Stat**	***p*-val**
dummy_winner	.326	.154	2.119	.038*	.120	.059	2.045	.045*
value_class	.137	.051	2.705	.009**	.070	.021	3.357	.001**
auction_sequence	-.125	.049	-2.579	.012*	-.047	.022	-2.180	.033*
c (constant)	1.844	.195	9.475	.001***	.902	.063	14.359	.001***

* $p < .05$, ** $p < .01$, *** $p < .001$

One might question whether the regret information (investigated in Chapter 2, might influence the physiological experience of winning and losing. In the presented experiment, the regret information was revealed, conditional on the treatment group (Loser Regret (LR), Winner Regret (WR), No Regret (NR)), subsequently after the result information. Table B.3 shows a set of regression tables which indicate that an assignment to one of the three experimental treatment conditions (LR, WR, NR) does not influence the SCR.amp to the auction outcome (i.e. both the variables dummy_LR and dummy_WR remain insignificant). Again, these regressions were conducted for two different baseline measures (ref_value and ref_result) and two alternatives for the influencing variables (value_class and avg_nom_payoff).

Table B.2.: Regression Models for Testing the Influence of Average Nominal Payoff and Value Classes (Standard Errors Adjusted for 59 Clusters in Subject)

	Dependent variables							
	SCR.amp (ref_value)				**SCR.amp (ref_result)**			
Independent variables	**B**	***p*-val**	**B**	***p*-val**	**B**	***p*-val**	**B**	***p*-val**
dummy_winner	.326	.038*	.418	.011*	.120	.045*	.153	.001**
value_class	.137	.009**			.070	.001**		
avg_nom_payoff			.026	.002**			.009	.009**
auction_sequence	-.125	.012*	-.136	.007**	-.047	.033*	-.052	.018*
c (constant)	1.844	.001***	1.568	.001***	.902	.001***	.858	.001***

* $p < .05$, ** $p < .01$, *** $p < .001$

With respect to SCR, a paired sample two-sided t-test shows that the difference in SCR.amp for different auction outcomes is significant (1.744 vs. 2.206, $n = 59$, $t = -3.543$, $p < .001$). Results of paired Wilcoxon Rank Sum test ($Z = -3.570$, $p < .001$, $r = .465$) are consistent with those findings.

Similar to the normalization for SCR.amp values, as described in Chapter 3, for robustness checks, we reference each of the 50 HR signals to the individual baseline of the average HR response to the valuation information. Subsequently, an average value is computed for each bidder for the event of winning and losing. More specifically, when analyzing the response to seeing the auction outcome, we first reference the HR signal to the moment that the auction outcome was revealed, and then divide the result by the absolute value of the drop in the subject's average heart rate upon receiving the valua-

Table B.3.: Experience of Regret Conditional on the Treatment Condition (Standard Errors Adjusted for 59 Clusters in Subject)

	Dependent variables							
	SCR.amp (ref_value)				SCR.amp (ref_result)			
Independent variables	**B**	***p*-val**	**B**	***p*-val**	**B**	***p*-val**	**B**	***p*-val**
dummy_LR	.313	.393	.236	.503	.025	.406	-.001	.963
dummy_WR	.181	.449	.216	.362	.016	.552	.027	.297
dummy_winner	.327	.041*	.416	.010*	.120	.046*	.153	.009**
value_class	.137	.010*			.070	.001**		
avg_nom_payoff			.026	.007*			.009	.018*
auction_sequence	-.125	.013*	-.135	.001*	-.047	.034*	-.052	.001**
c (constant)	1.188	.053	.978	.126	.848	.001***	.820	.001***

* $p < .05$, ** $p < .01$, *** $p < .001$

tion information. We have included two additional columns which report the results of a t-test and a paired Wilcoxon Rank Sum test (Table B.4).

Table B.4.: Analysis of Normalized (ref_value) Phasic Changes in HR in Response to Winning and Losing ($n = 66$)

Seconds after Auction Outcome	Mean Difference in HR (lose-win)	*t*-test *p*-value	Wilcoxon *p*-value
1.0	-.45	.339	.189
1.1	-.81	.092	.099
1.2	-1.15	.028*	.074
1.3	-1.54	.017*	.025*
1.4	-1.88	.008**	.009**
1.5	-2.20	.006**	.005**
1.6	-2.59	.006**	.001**
1.7	-2.83	.003**	.001**

* $p < .05$, ** $p < .01$, *** $p < .001$

B.2. Supplementary Analyses for Chapter 4

Table B.5 depicts a factor analysis of the German version of the ERQ (Abler and Kessler, 2009; Gross and John, 2003).

Table B.5.: Varimax Rotated Factor Loadings for the 10 Items of the Emotion Regulation Questionnaire (ERQ) ($n = 104$)

Item	**Cronbach's Alpha**	**Factor 1**	**Factor 2**
Cognitive Reappraisal 1	.712	**.358**	-.226
Cognitive Reappraisal 2		**.512**	-.214
Cognitive Reappraisal 3		**.467**	.063
Cognitive Reappraisal 4		**.699**	-.099
Cognitive Reappraisal 5		**.589**	.107
Cognitive Reappraisal 6		**.602**	.110
Suppression 1	.648	-.006	**.561**
Suppression 2		-.191	**.569**
Suppression 3		-.008	**.616**
Suppression 4		-.003	**.429**
Eigenvalue		**1.890**	**1.296**
Variance Explained (per cent)		**.189**	**.130**
Cumulative Variance Explained (per cent)		**.189**	**.319**

Eigenvalues were extracted according to the Kaiser criterion. As depicted in Table B.5 not all items load properly on the respective constructs and have only little mean cross-loading of -.046. Cronbach's alphas exceed only for Cognitive Reappraisal the critical value of .70, however, not for suppression (.648). For this reason, the factors retained by the factor analysis are not further employed in the following analysis.

Table B.6 provides a regression analysis for all subjects, invariably of whether physiological measurements could be assessed or not. As a comparison with Table 4.1 shows, the results remain robust.

Table B.6.: Regression Tables For Bids. Note: The Regressions are Based on Robust Standard Errors Clustered by 70 Subjects.

	Dependent variables				
	Bid				
Independent variables	**B**	**SE**	***t*-Stat**	***p*-value**	
value	.534	.035	15.170	<.001	***
dummy_competition (CMP)	-2.971	.980	-3.031	.003	**
suppression	1.304	.507	2.573	.012	*
CMP x suppression	-2.639	.899	-2.934	.005	**
reappraisal	.819	.456	1.798	.076	
CMP x reappraisal	.085	1.050	.081	.935	
safe_choices	.792	.288	2.747	.008	**
dummy_gender_female	.352	1.293	.272	.786	
auction_round	.037	.061	.597	.552	
constant	12.580	3.077	4.088	<.001	***
	$n = 1047$				
	$R^2 = .343$				

* $p < .05$, ** $p < .01$, *** $p < .001$

B.3. Supplementary Analyses for Chapter 5

In this section we list complementary analyses and robustness checks for the statement that ER and arousal influence decision performance in the Auction Game when used as a onetime intervention.

In Evaluation Study I participants played the Auction Game and filled out the ERQ (Abler and Kessler, 2009; Gross and John, 2003) at the end of the experiment. As mentioned previously, in Evaluation Study II the Auction Game was followed by several other games. Due to these constraints the ERQ was assessed before the game sessions had started. Even though the ERQ is intended to measure reappraisal and suppression as trait variables, which should not be influenced by chronological execution, it turns out that subjects' average ER score in Evaluation Study I is significantly different from Evaluation Study II. However, there is no difference in overall game performance (.701 vs. .688, $n = 80$, $t(78) = .480$, $p = .632$) nor in arousal (3.258 vs. 2.871, $n = 80$, $t(78) = 1.393$, $p = .168$) between the two studies.

As a robustness check for the influence of ER on decision performance, we employ a normalized ER score *(ER score (norm))*. For this measure we inherently assume that subjects' ER capacities in the two evaluation studies are on average the same.

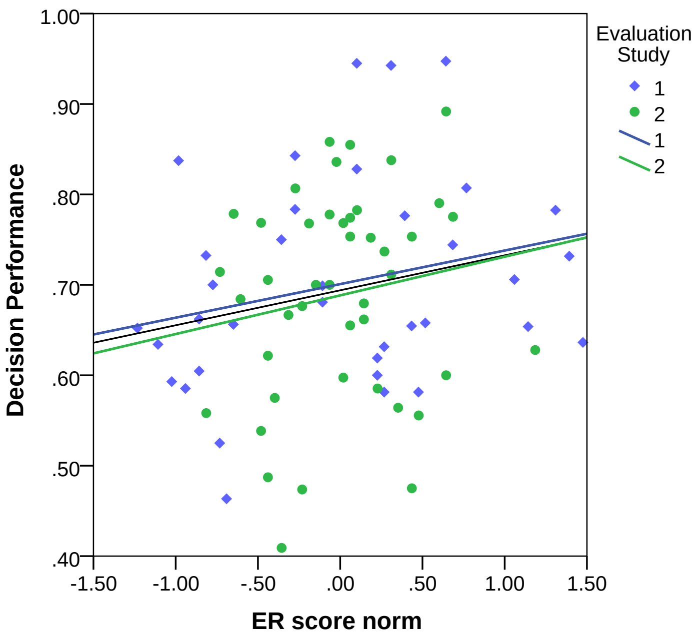


Figure B.1.: Correlation of Decision Performance and ER Score Norm ($n = 80$).

Figure B.1 illustrates the correlation of the normalized ER score and participants' decision performance for both evaluation studies independently.

The following set of regressions in Table B.7 also confirms that the results are invariably robust against usage of *ER score* or *ER score norm* with respect to arousal and ER.

Table B.7.: Regression for Subjects' Decision Performance on Arousal, Varying Measures for ER and Control Variables for Subjects being in the NBF Treatment or in Evaluation Study II ($n = 80$).

	Decision Performance									
Independent variables	**B**	**SE**	***t*-Stat**	***p*-value**		**B**	**SE**	***t*-Stat**	***p*-value**	
arousal	-.032	.009	-3.370	.001	**	-.032	.009	-3.370	.001	**
ER score	.041	.019	2.132	.036	*					
ER sc. (norm)						.041	.019	2.132	.036	*
dummy NBF	-.091	.034	-2.640	.010	*	-.091	.034	-2.640	.010	*
dummy st. II	-.034	.034	-0.982	.329		-.073	.030	-2.464	.016	*
c (constant)	.858	.068	12.561	<.001	***	.925	.062	15.000	<.001	***

* $p < .05$, ** $p < .01$, *** $p < .001$

In the two evaluation studies the Emotion Regulation Questionnaire (ERQ) by Gross and John (2003) and its validated German translation by Abler and Kessler (2009) was used. In order to test for convergent and discriminant validity of the assumed constructs, a factor analysis is conducted.

Table B.8.: Varimax Rotated Factor Loadings for the 10 Items of the Emotion Regulation Questionnaire ($n = 104$)

Item	**Cronbach's Alpha**	**Factor 1**	**Factor 2**
Cognitive Reappraisal 1	.834	**.732**	.079
Cognitive Reappraisal 2		**.816**	-.068
Cognitive Reappraisal 3		**.420**	-.003
Cognitive Reappraisal 4		**.730**	.076
Cognitive Reappraisal 5		**.585**	.196
Cognitive Reappraisal 6		**.768**	.212
Suppression 1	.745	-.005	**.687**
Suppression 2		-.008	**.655**
Suppression 3		.097	**.743**
Suppression 4		.218	**.508**
Eigenvalue		**3.099**	**1.611**
Variance Explained (per cent)		**.310**	**.161**
Cumulative Variance Explained (per cent)		**.310**	**.471**

Table B.8 depicts the results of the conducted factor analysis in order to retain values for the constructs *cognitive reappraisal* and *suppression*. Eigenvalues were extracted according to the Kaiser criterion. All items load properly towards the respective constructs and have only little mean cross-loading of .096. Cronbach's alphas exceed .700. The results confirm discriminant and convergent validity of the constructs and are comparable with the findings of Gross and John (2003). Analogously to the ER score we use the retained factors in the following regressions in a measure that reflects both strategies equally, the *ER score (factor analysis (fa))*.

Table B.9 depicts a set of OLS regression tables employing the *ER score* and the *ER score (fa)*. As can be seen the influence of ER on decision performance remains both (marginally) statistically and economically significant for both measures.

Table B.9.: Regression for Subjects' Decision Performance on Arousal and Varying Measures for ER ($n = 80$).

	Decision Performance									
Independent variables	**B**	**SE**	***t*-Stat**	***p*-value**		**B**	**SE**	***t*-Stat**	***p*-value**	
arousal	-.032	.009	-3.370	.001	**	-.032	.009	-3.354	.001	**
ER score	.041	.019	2.132	.036	*					
ER score (fa)						.043	.023	1.905	.061	+
dummy NBF	-.091	.034	-2.640	.010	*	-.088	.035	-2.543	.013	*
dummy st. II	-.034	.034	-0.982	.329		-.034	.035	-.970	.335	
c (constant)	.858	.068	12.561	<.001	***	.859	.070	12.273	<.001	***

$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

The same set of regressions for the No Influence (NI) version of the Auction Game confirms that here, neither ER nor arousal significantly influences decision performance (see Table B.10).

Table B.10.: Regression for Subjects' Decision Performance on Arousal and Varying Measures for ER in the NI treatment ($n = 24$).

	Decision Performance									
Independent variables	**B**	**SE**	***t*-Stat**	***p*-value**		**B**	**SE**	***t*-Stat**	***p*-value**	
arousal	-.020	.023	-.893	.382		-.019	.023	-0.834	.413	
ER score	-.089	.074	-1.193	.246						
ER score (fa)						-.080	.084	-.951	.352	
c (constant)	.667	.102	6.539	<.001	***	.673	.105	6.440	<.001	***

* $p < .05$, ** $p < .01$, *** $p < .001$

Finally, subjects' average arousal scores are not correlated with subjects' ER scores ($n = 104$, Pearson's $r = -.053$, $p = .595$). This provides evidence that both subjective and objective ER capacities are independent and indeed separate constructs of emotional processing.

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List of Abbreviations

ACM	Association for Computing Machinery
Ag	Silver
AgCl	Silver Chloride
ANOVA	Analysis of Variance
ANS	Autonomous Nervous System
BF	Biofeedback
BPM	Beats per Minute
CMP	Competition (Images) Treatment
COM	Community (Images) Treatment
CRRA	Constant Relative Risk Aversion
DE	Direct Effect
ECG	Electrocardiogram
ECIS	European Conference on Information Systems
EDA	Electrodermal Activity
Eds.	Editors
EEG	Electroencephalography
ER	Emotion Regulation
ERQ	Emotion Regulation Questionnaire
fMRI	functional Magnetic Resonance Imaging
FoL	Frustration of Losing
FPSB	First-Price Sealed-Bid
FS	Field Study
HR	Heart Rate
HSD	Honestly Significant Difference
IAPS	International Affective Picture System
ICIS	International Conference on Information Systems
IE	Indirect Effect
IISM	Institute of Information Systems and Margeting
IME	Information and Market Engineering
IPV	Independent Private Value
IT	Information Technology
JoW	Joy of Winning
KIT	Karlsruhe Institute of Technology
LE	Laboratory Experiment
LL	Lower Level
LR	Loser Regret

M	Mean
μS	Microsiemens
MIS	Management of Information Systems
ME	Moderating Effect
MU	Monetary Unit
NBF	No Biofeedback
NI	No Influence
NM	Neuroscience Methods
NO	No (Images) Treatment
NR	No Regret
OLS	Ordinary Least Squares
OSEA	Open Source ECG algorithm
PLoS	Public Library of Science
PNAS	Proceedings of the National Academy of Sciences
RNNE	Risk Neutral Nash Equilibrium
RV	Review
s	Seconds
SC	Skin Conductance
SCL	Skin Conductance Level
SCR	Skin Conductance Response
SCR.amp	Skin Conductance Response Amplitude
SD	Standard Deviation
SE	Standard Error
SFB	Sonderforschungsbereich
SSRN	Social Science Research Network
SV	Survey
TAM	Technology Acceptance Model
TE	Total Effect
TM	Theoretical Model
UL	Upper Level
WR	Winner Regret

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List of Symbols

v_i	independent private value of bidder i
b_i	bid of bidder i
$b_i(v_i)$	bidding function of bidder i
z	highest bid made by the competitors
F	cumulative distribution function of z
α	parameter for loser regret
β	parameter for winner regret
p_i	nominal payoff
Π_i	profit of bidder i
$b(v_i)^*$	optimal bidding strategy
x	integer variable
B	regression coefficient
se	standard error
t	t-statistics
p	p-value
c	constant
n	number of participants
r	Pearson's correlation coefficient
ΔHR	drop in heart rate
ΘHR	ratio of subjects' HR to baseline HR

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Affidavit

I hereby affirm truthfully that this thesis has been written only by the undersigned and without any assistance from third parties. Furthermore, I confirm that no resources have been used in the preparation of this thesis other than those indicated in the thesis itself, including quoted and adapted contents of publications from other authors and myself.

Eidesstattliche Erklärung

Ich versichere wahrheitsgemäß, die Dissertation bis auf die in der Abhandlung angegebene Hilfe selbständig angefertigt, alle benutzten Hilfsmittel vollständig und genau angegeben und genau kenntlich gemacht zu haben, was aus Arbeiten anderer und aus eig enen Veröffentlichungen unverändert oder mit Abänderungen entnommen wurde.

Karlsruhe, 2013

(Philipp J. Astor)