Understanding and Supporting Decision-Making in Electronic Auctions: A NeuroIS Approach

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Karlsruhe, June 2016 Marius B. Müller

Contents

Part I.

Introduction

Chapter 1.

Introduction

Access to information hidden within human physiological data was long privileged to medicine and professional sports. Recently, however, advances in sensor technology enabled real-time recording and analyses of human physiology, even for average consumers. Nowadays, sensors are smaller, more accurate, and more affordable than ever before—and they become increasingly ubiquitous (Al Osman et al., 2014). This not only relates to fitness trackers, which are now used by millions of fitness enthusiasts on a daily basis. Also sensors measuring, for example, heart rate and skin conductance, are increasingly integrated in more devices that surround people's everyday lives, such as smartphones, smart wearable devices, and, in the near future, middle class cars (Audi AG, 2016) and clothing (Tsukada et al., 2014).

Access to physiological data can provide great insights into a human's inner state, their emotions, and ultimately can further the understanding of human behavior and the inner processes that drive decision-making. As *"important decisions induce powerful emotions in decision-makers"* (Loewenstein, 2000, p. 429), understanding the role of emotions can bring new insights to empirical evidence that often shows behavior differ from theoretical expectations. Especially, in the context of economic decision-making, such as electronic auctions, where most decisions are important due to their long-lasting, irreversible, and financial consequences. Here, understanding the role of emotions can aid the improvement of theories and create tangible monetary benefits by supporting decision-making (Lucey and Dowling, 2005).

In order to make use of such advantages, decision-makers require support systems that can automatically record, analyze, and act based on decision-makers' current physiological data—preferably all in real-time. Even at the most advanced electronic auctions, the financial trading industry, supporting human decision-makers becomes increasingly of interest. Thereby, *"[a] lot of smart managers think their [algorithms] have gone as far as they can go. The next step is human optimization"* (Solon, 2015). But also in non-professional auction environments, such as retail auctions, decision-makers can benefit from using support systems. By using the valuable information of their physiological data, decision-makers can use tools and methods, such as Neuro-Adaptive Information Systems (IS) and Live-Biofeedback (LBF), to control their actions, increase their self-awareness, and train their self-regulating abilities in order to decrease biases in their decision-making (Astor et al., 2014).

To this end, the aim of this thesis is to contribute to the understanding and supporting of decision-making in electronic auctions by applying new NeuroIS methods that use insights derived from human physiological data.

1.1. Human Decision-Making in Electronic Auctions

Based on classical economic literature, decision-making in electronic auctions follows a calculating and emotionless process. Factors, such as (personal) costs and payoffs, are frequently named as driving forces that lead decision-makers. Even as, over the last decades, decision-making in electronic auctions became more and more complex and cognitively demanding (e.g., more decisions, more information, and less time to decide), in theory, decisions are made by *"the well informed, rational, utility maximizing"* (Rothkopf, 1991, p. 40) Homo Economicus. This theoretical concept *"has generally been depicted as a supra-rational, self-interested breed that possesses immense foresight and cognitive abilities [...] but at the same time, 'devoid of emotions'"* (Lee et al., 2009, p. 183).

In contrast to this concept, an increasing number of empirical studies showed that decision-making does not exclusively follow the rationale of the Homo Economicus (Henrich et al., 2001; Gintis, 2000). For example, effects such as winner's curse (Kagel and Levin, 1986), bidder's curse (Malmendier and Lee, 2011), and quasi-/pseudo endowment (Heyman et al., 2004) contradict the concept of the Homo Economicus. Such effects were even found in environments that are commonly described to be very calculating and emotionless, such as financial markets, where studies revealed decision-makers' behavior that is more driven by *'gut feeling'* than theoretical expectations (Fenton-O'Creevy et al., 2011, 2012). These and similar findings furthered the opinion that *"Homo Economicus will become more emotional"* (Thaler, 2000, p. 139) or even that the *"Homo Economicus is a fiction that can no longer be maintained in light of mounting evidence to the contrary"* (Lo, 2010, p. 5).

One common explanation for the empirical findings in decision-making is based on *dual system* models in which the complex interplay between cognitive and affective processes drive decision-making. The models usually distinguish between an analytic cognitive system and an emotionally charged affective system (e.g., system 1/system 2 (Kahneman, 2003), reflexive/reflective system (Lieberman et al., 2002), or experiential/rational system(Epstein, 1994)). Depending on the situation, each system can play a dominant role in determining human behavior and, therefore, decision-making. Neuroscientifically, the two systems can be located in different areas of the brain. Whereas cognitive and more controlled processes are located in the frontal regions of the brain (orbital and prefrontal), the system for affective and automatic emotional responses is located in the limbic system (primarily amygdala and anterior cingulate) (Damasio, 1994). Although, these models are oversimplified representations of human decision-making, the general distinction between cognition and emotion provides great value in explaining empirical findings in decision-making (Lee, Amir, and Ariely, 2009).

Building on the concept of emotions as an influencing aspect, a few frameworks exist that include emotions in the process of decision-making in auctions. The emotion-decision framework for emotional bidding (Adam et al., 2011), for example, not only includes the economic environment. The framework also includes the emotional state and the influence of auction events on emotions into the decision-making process, in order to formally structure theoretical and empirical evidence of bidding behavior in auctions. Although, nowadays, emotions are seen as a factor that deviates decision-making from a theoretical expectation based on optimal bidding functions, such as the ones in Vickrey (1961) and Kagel and Levin (1986), the influence of emotions on decision-making has shown to be neither exclusively bad nor good (Seo and Barrett, 2007).

In order to empirically research the influence of emotions, emotions need to be recorded, often in an unobtrusive manner. To this end, physiological changes in the human body (e.g., racing heart or shortness of breath) can be recorded as they are elicited by emotions—making them a machine-readable proxy for current emotions. The measurements reflect intensity (i.e., arousal) and/or valence (i.e., positive or negative).

Both provide valuable insights into the understanding of how and in what way emotions influence decision-making (not only in electronic auctions).

Studies have shown that, for example, physiological arousal induced by stress (Oberlechner and Nimgade, 2005), or competitive arousal induced by competition (Malhotra, 2010), can have negative biasing effects on decision-making. But also incidental influences (i.e., seemingly irrelevant aspects of the environment), such as temperature, colors, and interface design elements, have been shown to influence decision-making (Storey and Workman, 2013, 2014; Riedl et al., 2011; Hawlitschek et al., 2016).

Therefore, in this thesis, we further investigate the influence of emotions on decision-making in electronic auctions. To this end, we investigate electronic auctions and include the measurement of physiological data into the research.

1.2. Physiological Data in Information Systems Research

One of the earliest concepts that combines computer research and the use of physiological information was stated by Picard (1995). The author's concept, called *Affective Computing*, combines all *"computing that relates to, arises from, or influences emotions"* (Picard, 1995, p. 1), which is based on a computer's ability to read a user's affective state and its ability to also have emotions. Also, in the late 1990s, initial attempts were made to create commercially available products that used physiological information. One example is the video game *Tetris 64*, released in 1998, that used an ear clip to measure a user's heart rate and that used this measurement to either speed up or slow down the game's speed. However, further products of such kind remained rare.

Lately, the use of physiological information in IS research has gained a strong momentum, due to reasons, such as increased availability of sensors (e.g., in smartphones and consumer fitness devices), advances in computer science and computational power, and decrease in cost-per-use of measurement devices.

Also, recently, a new dedicated subfield in IS research emerged, called NeuroIS (Dimoka et al., 2007), that uses physiological theories, methods, tools, and measurements to better understand the design, development, and use of IS (Dimoka et al., 2011, 2012), as well as IS phenomena, such as technostress and flow (Adam et al., 2016; Riedl et al., 2012). Due to the use of neuroscience and (neuro-)physiology, NeuroIS is able to provide insights into visceral and previously hidden processes of the human body that influence user behavior and the way users and computer interact (i.e., Human-Computer Interaction (HCI)). Especially, since many aspects of user behavior occur instinctively and unconsciously, users are often not aware of such aspects and, therefore, are not able to verbalize nor actively control these aspects. The NeuroIS approach complements this downside (Tams et al., 2014), which affects traditional methods for collecting survey data, such as questionnaires and interviews. Therefore, physiological data and its use in IS are seen as a complement to existing IS research methods—not a replacement.

Although, the name NeuroIS might suggest that data used in NeuroIS research is limited to neurological data (i.e., brain activity, such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), near-infrared spectroscopy (NIRS)), NeuroIS also considers all other physiological data, such as heart rate, skin conductance, and respiration (Riedl et al., 2009; Dimoka et al., 2012). Especially, the later are increasingly used in research as the necessary sensors are more available and ready to use due to the previously stated reasons.

In addition to the physiological data, NeuroIS research also considers a user's behavioral data, i.e., interaction with the IS, such as decisions, mistakes, and task performance. The combination of these types of data is an interdisciplinary approach that brings great potential for research and practitioners. Especially, in the highly computerized and fast-paced environment of electronic auctions, decision-makers can benefit from the potential of NeuroIS. Here, decision-making is constantly influenced by conscious and unconscious biases that can be researched and possibly addressed through appropriately designed user interfaces and decision-support systems.

For example, a recent NeuroIS publication show the possibility of using LBF on a financial trading floor (Fernández et al., 2013). LBF is a method in which a decision-maker's physiological data is recorded and immediately fed back to the decision-maker in real-time, using various kinds of feedback methods, such as visual, auditory, and tactile feedback. The paper showed that using LBF can increase traders' awareness for their current (and previously unknown) stress level and reduce the likelihood of poor decision-making, i.e., reduce risky decision-making. Similarly, a study in the serious games context showed how LBF can be used to train emotion regulation capabilities in financial decision making (Astor et al., 2013).

Hence, making use of the potential of NeuroIS, we apply a NeuroIS approach in this thesis to further the understanding of decision-making and to analyze the opportunities for NeuroIS in decision-support, both in electronic auctions.

1.3. Research Outline and Structure

The goal of this thesis is to better understand decision-making in electronic auctions by using a NeuroIS approach and to utilize this understanding to provide support for decision-makers in the future. The work at hand comprises four parts as shown in Figure 1.1.

Part I motivates this thesis, outlines the structure of this thesis, and presents the examined research questions. Part II focuses on understanding the interplay of arousal, physiology, and decision-making in electronic auctions. The part is structured in two chapters (Chapter 2 and Chapter 3) that are partially based on the joint paper *"Auction fever! How time pressure and social competition affect bidders' arousal and bids in retail auctions"* with Marc T.P. Adam and Jan Krämer. The paper was published in the *Journal of Retailing* in 2015 (Adam, Krämer, and Müller, 2015). Electronic auctions on the Internet frequently put bidders under time pressure or highlight the social competition that is inherent to auctions. Both aspects are believed to elicit an exciting shopping experience, which may culminate in auction fever. The process of auction fever is investigated using ascending clock auctions, commonly used in retail auctions, in two laboratory experiments. The laboratory experiments are conducted to understand and demonstrate when and how auction fever affects bidding behavior, i.e., decision-making.

Chapter 2 presents the first of two laboratory experiments. It uses physiological measurements (heart rate and skin conductance measurements) to capture the bidders' physiological arousal. Physiological arousal is used to objectively measure the effect of auction fever on bidders' physiology and bidding behavior. Thus, Chapter 2 focuses on Research Question 1, which states:

> **Research Question 1:** *Can physiological measurements provide evidence for the phenomenon of auction fever in ascending auctions?*

In order to further investigate the findings of Chapter 2, Chapter 3 presents the second laboratory study that examines auction fever. This laboratory study is also set in an ascending clock auction environment, but focuses on using psychometric measurements that are collected by using self-reported questionnaires. Avatars, which are stylized graphical representations of the bidders (Teubner et al., 2014), were used to stimulate bidders' competitive arousal. Using these measurements, the insights of Chapter 2 are complemented by further investigating bidders' perceptions of competitive arousal in order to identify the actual drivers of their physiological arousal and the influence on decision-making. Thus, Chapter 3 focus on Research Question 2, which states:

> **Research Question 2:** *How is competitive arousal perceived in the social competition of ascending auctions and what is its impact on bidding?*

Part III focuses on utilizing the insights gained in Part II and recent NeuroIS research in order to support decision-making in electronic auctions. As there are biases in decision-making that are well identifiable using NeuroIS methods, these methods can also be used to support decision-makers and create support systems. However, applying NeuroIS methods to support decision-making poses new challenges that are addressed in Part III. To this end, the part is structured in two chapters (Chapter 4 and Chapter 5). Chapter 4 demonstrates a methodological approach for selecting useful physiological measurements for a given context and Chapter 5 provides an introduction of LBF in the context of IS research.

Parts of Chapter 4 are based on the joint paper *"Selecting physiological features for predicting bidding behavior in electronic auctions"* with Marc T. P. Adam, David J. Cornforth, Raymond Chiong, Jan Krämer, and Christof Weinhardt. The paper was presented at the *Hawaii International Conference on System Sciences 2016* (Müller et al., 2016) and nominated for the best paper award. Previous research has shown that affective processes play an important role in determining decision-making in electronic auctions and that physiological measurements provide insights into a decision-maker's affective processes. However, it remains unclear which of the thousands of features that can be computed from physiological data at each moment are particularly useful in predicting human behavior. Identifying these features is important for gaining a better understanding of affective processes in electronic auctions and for building support systems, such as biofeedback systems. Chapter 4 proposes a new approach to identify physiological features for predicting decision behavior in electronic auctions. An evolutionary algorithm is applied in combination with either multiple linear regressions or artificial neural network models to select physiological features and assess their predictive power. Evolutionary algorithms are population-based metaheuristics that are able to find optimal solutions in a complex search space by starting with randomly initiated solutions and evolving them over time. To test the approach, the data set of the study in Chapter 2 is used, as the data set comprises of electrocardiography (ECG) data and synchronously recorded auction decisions. Thus, Chapter 4 focuses on Research Question 3, which states:

> **Research Question 3:** *How can evolutionary algorithms be used to select physiological features for predicting bidding behavior in electronic auctions?*

Chapter 5 reviews LBF in the context of IS research and its potential for building LBF support systems. Parts of Chapter 5 are based on the joint paper *"A NeuroIS Platform for Lab Experiments"* with Anuja Hariharan and Marc T. P. Adam, which was presented at the *Gmunden Retreat on NeuroIS 2014* (Müller et al., 2014). LBF systems are a subcategory of Neuro-Adaptive ISs (and NeuroIS in general) that use a person's physiological measurements to create an instant (i.e., live) feedback of physiological data. The measurements can include a single or any combination of multiple physiological measurements, such as heart rate, skin conduction, and respiration. The implemented LBF can also consist of a single or multitude of outputs, such as visual, auditory, and tactile. In contrast to Neuro-Adaptive ISs, which modify system properties based on the person's physiological measurements, LBF systems only use the physiological measurements to create feedback—but not to modify other properties of the IS. However, using LBF can support a person in adapting themselves in order to induce behavioral change in a given context. In the context of decision-making in an electronic auction, LBF has been shown to generally reduce behavioral biases (e.g., winner's curse and quasi-/pseudo-endowment). In order to gain a better understanding of the systematical effects and potential of LBF as support system, a integrative theoretical framework is proposed. Therefore, this section builds on existing literature to derive the framework that shows established relation of a decision-maker's environment, affective state, and behavior. The framework also proposes three moderating influences of LBF and how to systematically research LBF moderations for decision support in electronic auctions and IS in general. Thus, Chapter 5 focuses on Research Question 4, which states:

Research Question 4: *How can Live-Biofeedback be used in NeuroIS research to support decision-making in electronic auctions?*

Finally, Part IV concludes this thesis by summarizing the findings and discussing their implications for research and practitioners. In addition, Part IV provides an outlook for future work in IS research as well as related research areas.

Part I **INTRODUCTION**	**Chapter 1** Introduction
Part II **UNDERSTANDING**	**Chapter 2** The Role of Physiological Arousal and Bidding Behavior
	Chapter 3 Competitive Arousal and Bidding Behavior in Ascending Auctions
Part III **SUPPORTING**	**Chapter 4** Predicting Bidding Behavior using Physiological Data
	Chapter 5 Using Physiological Feedback in IS Research
Part IV **FINALE**	**Chapter 6** Conclusion and Future Research

Figure 1.1.: Structure of this thesis.

Part II.

Understanding

Chapter 2.

The Role of Physiological Arousal and Bidding Behavior

In this chapter, we seek to clarify the role of arousal and its impact on bidding behavior in electronic auctions. More precisely, we seek insights into what actually drives bidders' physiological arousal and how this physiological arousal affects bidding behavior. To this end, we investigate the phenomenon known as auction fever using ascending clock auctions in a controlled lab environment. Thus, this chapter investigates Research Question 1, which states:

> **Research Question 1:** *Can physiological measurements provide evidence for the phenomenon of auction fever in ascending auctions?*

2.1. Introduction

Internet auctions have become an important pillar for online retailers to sell their products. Rather than simply buying products online, participants of Internet auctions can experience the competitive atmosphere of interacting with other bidders and the exhilarating feeling of winning the inherent social competition. Thus, in comparison to fixed-price offers, auctions have the potential to provide an exciting shopping experience, i.e., to evoke emotions and high levels of arousal throughout the auction process. The hedonic value that is derived from this fun and excitement is even believed to be the actual reason for the success of Internet auctions (Ariely and Simonson, 2003; Childers et al., 2001). Correspondingly, Internet auction sites for consumers are often explicitly designed to elicit excitement in the bidders.

Towards this end, many online retailers deliberately focus on dynamic auctions as they provide more time for the intended emotional processes to unfold in the dynamic interaction of competitive bidding (Ariely and Simonson, 2003; Ku et al., 2005). Second, they employ design elements that induce a strong sense of time pressure in the bidders. For example, during the last minute of an auction on ebay.com, the remaining time is shown in red characters and updated every second. On other sites, such as madbid.com, the auctions that are ending soon are displayed on the starting page and their remaining time is highlighted by a red color. Third, Internet auction sites boost the degree of social competition among the bidders by highlighting the presence of other human bidders. On dealdash.com, for example, bidders can choose an avatar that is displayed next to their nickname. The exciting features of dynamic auctions are also directly addressed on the websites and in the advertisement campaigns of Internet auction platforms. In Australia, for instance, eBay launched an advertisement campaign in 2008 with the title "Make shopping exciting!" (eBay Inc., 2007b) . Likewise, madbid.com and dubli.com directly promote themselves as entertainment shopping platforms to attract customers.

While the fun and excitement derived from Internet auctions has been found to be a source of hedonic value for the consumers, it has also been conjectured that the induced levels of arousal may in turn have detrimental effects on the consumers' bidding behavior. (Murnighan, 2002, p.63), for example, noted that in the heat of the moment, the bidders' "adrenaline starts to rush, their emotions block their ability to think clearly, and they end up bidding more than they ever envisioned." This auction fever phenomenon has two distinct characteristics. First, under auction fever bidders experience an intense emotional state (referred to as "arousal"), and second, auction fever is associated with irrational bids and higher prices in ascending auctions (Jones et al., 2011; Malmendier and Lee, 2011). In other words, the term auction fever implies that bidding is distorted because the bidders are emotionally aroused (Adam et al., 2011). It is notoriously hard, however, to provide empirical evidence for this phenomenon and thus it is an ongoing debate whether auction fever really exists or whether irrational bidding can be fully traced back to alternative explanations (Jones, 2011; Malmendier and Lee, 2011; Malhotra, 2010).

In this chapter, we seek to clarify the existence of the auction fever phenomenon and to provide further insight into what the drivers of bidders' arousal actually are. To this end, we investigate auction fever by employing a controlled lab environment. In the lab, bidders' valuations are known and bidders' arousal can be assessed with both objective and subjective measures. In particular, we conduct a lab experiments in which we assess bidders' arousal with physiological measures. Thereby, we focus specifically on time pressure and the inherent social competition of auctions, as these factors are considered to be the main drivers for so-called competitive arousal, which may ultimately lead to auction fever (Ku et al., 2005; Malhotra, 2010). In the experiments, we conduct ascending clock auctions in which the standing price increases at fixed time intervals and each bidder can choose to drop out of the auction at each bidding increment. The auction ends when only one bidder remains in the auction. This bidder acquires the commodity for the standing price at which the last but one bidder left the auction. The format of the ascending clock auction, which is sometimes also referred to as the English clock auction or Japanese auction (Milgrom and Weber, 1982), is a derivative of the English auction and has strong similarity to the proxy auction used on eBay and other retail auction sites (Klemperer, 1999).

This chapter makes four core contributions. First, the results of the lab experiment consistently show that bidders' arousal levels are significantly higher (i) in auctions with high time pressure and (ii) when the level of social competition is high. Second, bidders place significantly higher bids in the high time pressure auctions. However, it is important to note that this holds only in the context of an actual social competition, i.e., when the bidders are competing with human opponents rather than with computer opponents. Consequently, we identify social competition as the true driver behind the auction fever phenomenon and rule out alternative explanations for the influence of time pressure on bids, because it is not the effect of time pressure per se, but the effect of time pressure in a social competition that drives these results. Third, the physiological data reveals that in the presence of a social competition the effect of time pressure on bids is partially mediated by the bidders' arousal levels. Taken together, this can be interpreted as empirical evidence for auction fever, which—to the best of my knowledge—has not been shown under controlled conditions in a lab environment before. Finally, we analyze the intensities of emotions in response to winning and losing an auction and find that the "joy of winning" is significantly stronger than the "frustration of losing" in ascending auctions. This is in stark contrast to previous findings with respect to descending auctions. We can therefore conclude that ascending auction formats have the potential to convey a more rewarding user experience to the consumers than descending auction formats.

2.2. Theoretical Background and Hypotheses

Classical auction theory assumes that bidding in an auction can essentially be boiled down to an ex-ante maximization of expected utility. However, as we will describe in this section, there is reason to believe that bidding is in fact a dynamic process, which involves both cognitive as well as emotional processes. Based on this rationale, Adam et al. (2011) proposed an emotional bidding framework that integrates the traditional microeconomic perspective with the emotional aspects of the bidding process. The authors defined auction fever as “an emotional state elicited in the course of one or more auctions that causes a bidder to deviate from an initially chosen bidding strategy” (p. 204). This definition of auction fever, which we also adopt here, links the rational decisions of utility maximizing agents to the emotionally charged decisions of excited bidders. In other words, auction fever is believed to be present when bidding behavior is mediated by a bidder’s emotional state. In some studies the terms auction fever and overbidding are used interchangeably. Linking auction fever directly to overbidding is misleading however. First, overbidding is determined with respect to some theoretical baseline (e.g., an equilibrium bidding strategy), which again rests on a set of strong assumptions (e.g., full rationality, risk-neutrality, and complete information about the other participants). If the baseline is too low, e.g., because bidders are risk loving, “overbidding” may be identified, although no “auction fever” was actually present. In reverse, if the baseline is too high, e.g., because bidders are risk averse, “overbidding” may not occur, although there might have been auction fever. Second, restricting attention to overbidding would neglect changes in the bidders’ emotional state, which is, according to the above definition, a necessary criterion for the existence of auction fever. Third, in the context of descending auctions, such as the Dutch auction, auction fever may also result in systematic “underbidding” (see below for a more detailed discussion) and thus “overbidding” does not even constitute a necessary criterion for the existence of auction fever. In the context of ascending auctions, which we consider here, this means that an increase in bidders’ arousal is associated with higher bids.

Before we continue, it is important to conceptually distinguish between immediate emotions, emotional states, and arousal: Whereas an immediate emotion is a short lived subjective experience in response to specific events (e.g., the joy of winning or the frustration of losing) (Rick and Loewenstein, 2010), the emotional state is a continuous construct that channelizes the influence of the volatile immediate emotions and affective cues during the course of an auction. Thus, in contrast to an immediate emotion, the emotional state is ongoing and "the individual is never without being in some emotional state" (Zajonc, 1984, p.21). Finally, arousal describes the intensity of an emotion (Russell, 1980). In principle, arousal can be used to describe both, an immediate emotion as well as the emotional state. In order to avoid such ambiguity, we denote only the intensity of the emotional state as arousal throughout.

Previous research has shown that interacting with an Internet auction site can induce immediate emotions and increased arousal levels in the user, which are subject to the design of the auction mechanism, the user interface, and further elements of the auction environment (Ding et al., 2005; Ku et al., 2005; Park et al., 2012). For instance, Smith and Dickhaut (2005) found that the ascending clock auction induces less arousal than the descending clock auction. There is reason to believe, however, that Internet auction sites cannot only induce arousal in the bidders, but that this can also have a definite effect on their bidding behavior. In this sense, Internet auction sites could have a direct influence on the emergence of auction fever, which would also have an immediate impact on revenues. For instance, Jones (2011) analyzed eBay auctions in which Amazon.com gift certificates were auctioned off. While the bidders actually could have directly purchased the gift certificates from Amazon.com with no additional costs, 41.4% of the auctions ended with winning prices that exceeded the face value of the certificates. Similarly, Malmendier and Lee (2011) found that in 42% of eBay auctions, the bidders paid more than in simultaneously listed fixed-price offers for the same product. While these studies clearly point to the existence of "overbidding," they cannot ultimately explain why and how it occurs, i.e., whether the observed overbidding is actually due to auction fever (i.e., mediated by arousal) or due to alternative explanations, e.g., search and transaction costs.

In the following, thus, we propose a lab experiment that shall clarify the existence of auction fever and provide further insight into its drivers. The complete research model and the underlying hypotheses are depicted in Figure 2.1. Next, we motivate each hypothesis by surveying the relevant literature along the path of the research model, i.e., along the dynamic process of auction fever.

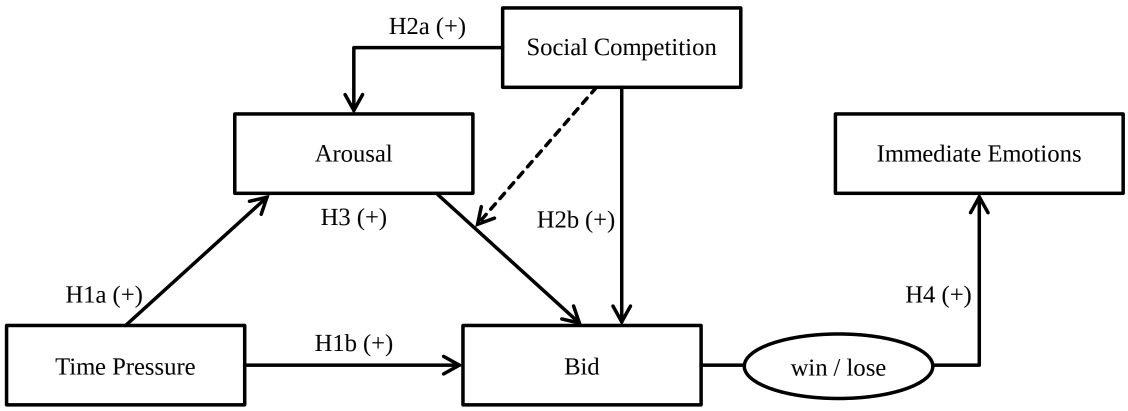


Figure 2.1.: Complete Auction Fever Research Model.

2.2.1. The Impact of Time Pressure on Arousal and Bids

As exemplified above, several Internet auction sites deliberately put their bidders under time pressure. While classical auction theory states that it should not make a difference for bidders whether an auction is static or dynamic (Vickrey, 1961), empirical research repeatedly showed that static and dynamic auctions yield different outcomes. The phenomenon of auction fever seems to only occur in dynamic auctions (Ockenfels and Reiley, 2006; Park et al., 2012). In particular, the seminal study by Cox et al. (1982) argued that time pressure is an important factor that drives decision making in auctions.

Several empirical studies investigated the relationship between time pressure and bidding in dynamic auctions. Haruvy and Leszczyc (2010) analyzed data from a local auction site and found that short auctions lead to more jump bidding activity, i.e., more aggressive bids, and consequently to higher prices in comparison to auctions with a longer duration. Ku et al. (2008) analyzed bidding behavior in an ascending auction under time pressure in a survey, i.e., where the participants stated hypothetical bids that did not affect their payoff, and found particularly high bids when bidders faced a high degree of time pressure and high stakes. Katok and Kwasnica (2008) investigated the impact of time pressure in descending clock auctions, where the auctioneer decreases the standing price until one of the bidders claims the good by accepting the current standing price. The authors found that bidders place lower bids under time pressure. Similarly, Cheema et al. (2012) found that time pressure can result in lower bids in descending auctions while it has the opposite effect in ascending auctions. Thus, with respect to whether time pressure increases or decreases final prices, it is crucial to differentiate between ascending and descending auctions. In both cases, these empirical results suggest that under time pressure bidders wait longer until they drop out of the auction. In a descending auction, this results in lower final prices and in an ascending auction, this results in higher final prices.

Psychologically, time pressure is known for fueling arousal and increasing the willingness of decision makers to take risks (Maule et al., 2000). For instance, Jones et al. (2011) showed that making lottery decisions under time pressure can be detrimental to decision performance and results in stronger arousal, as measured by increased heart rate as well as stronger activation in the brain regions insula and striatum. These brain regions are known to be activated when experiencing affective feelings and making choice selections, respectively. Finucane et al. (2000) found that when human decision makers face time pressure, they have a general tendency to rely on affect, which in turn is accompanied by increased arousal levels. In the context of auctions, Ku et al. (2005) and Malhotra (2010) argued that time pressure can fuel bidders' arousal. Based on these insights, the first research hypothesis states:

> **Hypothesis 1 (H1):** *Under the influence of higher time pressure levels, bidders (a) experience more arousal and (b) place higher bids in ascending clock auctions.*

2.2.2. The Impact of Social Competition on Arousal and Bids

In addition to putting bidders under time pressure, Internet auction sites frequently also emphasize the social competition that is inherent to auction participation. On eBay, for example, the bid history is accessible during the auction process along with a list of pseudonymized bidder identities. The platforms dealdash.com and madbid.com prominently display the nickname of the current highest bidder on the bidding screen. On the one hand, these design elements can increase the level of social presence on the platform and, thereby, improve the customers' shopping experience (Cyr et al., 2009; Hassanein and Head, 2006). On the other hand, these elements might also be a source of arousal, as previous research found that humans experience increased arousal levels when directly competing with other humans.

For instance, Sanfey et al. (2003) found in an ultimatum game bargaining experiment that human decision makers exhibited stronger activation in brain regions related to emotions when receiving unfair offers from human opponents rather than from computer opponents. With respect to trust in online markets, Riedl et al. (2011) found that the mentalizing network—a network of brain regions critical for social comparisons (Muscatell et al., 2012)—is more strongly activated when a human decision maker speculates about the trustworthiness of a human interaction partner rather than a computer agent. In the context of auctions, Ku et al. (2005) argued that interpersonal rivalry can induce a state of competitive arousal in bidders, which is particularly strong when time pressure is high. (Malhotra, 2010, p.140) defined competitive arousal as "an adrenaline-laden emotional state that can arise during competitive interaction." Thereby, the intensity of the social competition plays a critical role. With respect to behavior, Kamins et al. (2011) found that bidders place more bids in the last moments of an auction, if the user interface conveys social cues, i.e., to display the number of active bidders and the names of their user accounts. Likewise, Young-Hoon Park and Bradlow (2005) found that competition intensity can boost overbidding. Based on these insights, the second research hypothesis states:

> **Hypothesis 2 (H2):** *Under the influence of higher social competition levels, bidders (a) experience more arousal and (b) place higher bids in ascending clock auctions.*

2.2.3. The Mediating Role of Arousal

In the heat of the moment, humans have a tendency to rely on their affective processes—particularly when they face time pressure (Ariely and Loewenstein, 2006; Finucane et al., 2000). With respect to auction fever, (Ku et al., 2005, p.93) hypothesized in their competitive arousal theory that arousal can impair the bidders' "decision-making, and push them to bid past their limits." Likewise, the definition of auction fever implies that arousal is not a mere by-product of the auction process, but that it may ultimately cause bidders to place higher or lower bids. If auction fever really exists, thus, we should observe that the effect of time pressure on bids is mediated by bidders' arousal.

There is reason to believe, however, that auction fever only occurs in the presence of a social competition, i.e., when bidders are interacting with other human bidders. Internet auctions inherently trigger social comparisons between bidders, as each bidder knows that there are other human bidders who want to have the same item (Stern and Stafford, 2006). Hence, winning an auction does not only imply that the item was acquired but also that all other human bidders have been defeated. On the contrary, losing implies that the bidder has been defeated. Due to this competitive setting, previous research argued that auctions have a social nature and that auction behavior is essentially a socially constructed behavior (Palmer and Forsyth, 2006; van den Bos et al., 2013), which can be stimulated by increasing the salience of the bidders' social status (van den Bos et al., 2013) Indeed, there exists evidence in psychological studies that auction fever is more pronounced when bidders perceived a higher degree of social competition (Heyman et al., 2004; Ku et al., 2005; Malhotra, 2010; Murnighan, 2002). Moreover, Ariely and Simonson (2003) conducted a survey among Internet auction participants and found that 76.8% of the respondents perceive the other bidders as "competitors." In this sense, participating in an auction seems to be perceived as a competitive game in which the inherent social competition can cause a strong desire to beat the opponents and experience the uniqueness of being first upon winning (Malhotra et al., 2008; Stafford and Stern, 2002). In the light of these results, Engelbrecht-Wiggans and Katok (2007) argued that theories, which build on the social competition of auctions, require inter-personal comparisons and, therefore, necessitate the presence of human opponents. Correspondingly, van den Bos et al. (2008) found for the case of (static) first-price sealed-bid (FPSB) auctions that overbidding virtually disappears when the bidders face computer opponents instead of human opponents. Also in other economic contexts, the presence of human counterparts was found to play a critical role. In an ultimatum game bargaining study, for instance, Sanfey et al. (2003) found that humans behave less impulsively to unfair offers when they are interacting with a computer opponent rather than with a human opponent.

Based on these insights, we seek to clarify whether arousal is in fact a mediator for the effect of time pressure on bids, as it is required for the existence of auction fever. Thereby, we conjecture that social competition is a necessary prerequisite for this relationship, i.e., we expect that auction fever does not occur if bidders interact with computer opponents instead of human opponents. Hence, the third research hypothesis states:

> **Hypothesis 3 (H3):** *In the presence of a social competition, arousal mediates the effect of time pressure on bids.*

2.2.4. Immediate Emotions in Response to the Auction Outcome

The single most salient and anticipated event of any auction and thus the most prominent emotional experience is the revelation of the auction outcome. Previous research found that seeing the auction outcome can induce considerable immediate emotions in the bidders. The emotions experienced in response to winning and losing an auction are usually referred to as the “joy of winning” and the “frustration of losing,” respectively (Astor et al., 2013; van den Bos et al., 2013). With respect to static auctions, Delgado et al. (2008) found in a brain imaging study that losing a FPSB auction induces a stronger level of frustration than merely losing a theoretically equivalent lottery. Highlighting the social nature of auctions, van den Bos et al. (2013) reported that winning and losing a FPSB auction correlates with activity in brain regions, which have been found to be related to social preferences. Based on physiological measurements, Astor et al. (2013) found that winning a FPSB auction induces stronger immediate emotions than losing.

While for static auctions it has consistently been shown that the joy of winning is stronger than the frustration of losing, the picture is more complex for dynamic auctions. In particular, Adam et al. (2012) observed the opposite pattern for descending clock auctions, where the frustration of losing is stronger than the joy of winning. The authors attributed this to the “click-to-win” characteristic of descending clock auctions, because a descending clock auction ends as soon as the first bidder decides to stop the clock. In the moment the bidder clicks on the “place bid” button, they can thus cognitively prepare to win the auction, whereas losing comes as an unpleasant surprise. In contrast, an ascending clock auction has an inherent “click-to-lose” characteristic as bidders actively decide to exit and, thus, lose the auction, whereas winning comes as a pleasant surprise. Based on this reasoning, we hypothesize that due to the nature of the ascending clock auction, the immediate emotions induced in response to winning are stronger than those induced by losing. Hence, the fourth research hypothesis states:

> **Hypothesis 4 (H4):** *Winning an ascending clock auction induces a stronger immediate emotion in the bidders than losing an ascending clock auction.*

2.3. Experimental Design

In order to systematically investigate the hypotheses outlined in the research model, we conduct a controlled lab experiment with physiological measurements. Study participants were randomly recruited from a pool of undergraduate students with an academic background in economics by using ORSEE (Greiner, 2004). Following the induced value theory of Smith (1976), all decision-making in this experiment is directly related to real monetary payoffs. This means that during the experiment, each participant has to accumulate so-called monetary units (MU), which are individually converted into real money and paid out in cash after the experiment. In this experiment, 1 MU is equivalent to € 0.20.

2.3.1. Treatment Structure

In the experiment, each participant takes on the role of a bidder in a series of 15 ascending clock auctions. We have deliberately chosen this auction format, because (i) it enables us to maintain a high level of experimental control in the lab and (ii) this format has strong similarities to the English auction, the proxy auction used on eBay, and the penny auction which is frequently used on entertainment auction platforms.

The experiment constitutes a 2 (time pressure) × 2 (social competition) factorial design and includes four treatments (cf. Table 2.1). The participants exclusively participate in one of the four treatments (between-subjects design). In all treatments, the auctioneer starts the auctions at an initial price p_{min} of 25 monetary units (MU) and then increases the current standing price consecutively by δ=1 MU per time interval τ. In the high time pressure (HTP) condition, the current standing price is increased every τ=0.5 seconds. In the low time pressure (LTP) condition, the time interval is set to τ=5.0 seconds. These time intervals are identical to those used by Adam et al. (2012). Moreover, trial experiments were conducted to ensure that participants are in fact able to stop the clock at a given price in the HTP condition.

In order to compare auctions with different levels of social competition, the participants either interact with other human opponents or with computer opponents. There are six participants in each session and three bidders in each auction. In the social competition (SCO) condition, the six participants of a session are randomly assigned to two groups of three bidders prior to every single auction (random stranger matching). Each group plays a single ascending clock auction independently with three bidders each. Thus, each bidder competes with two other human bidders but does not know which of the other participants are currently participating in the same auction. In the no social competition (NSC) condition, each bidder competes with two computerized bidders. The participants are informed about the nature of their opponents (human or computer), but were given no information about the strategies of their opponents. In order to make the results comparable across treatments, the computer opponents replicate the bids of the human bidders as collected in the social competition treatments (see van den Bos et al. (2008) for a similar approach). Therefore, first the social competition sessions were conducted and then the no social competition sessions.

The auction is finished as soon as two of the three bidders decide to drop out of the auction. The winning bidder receives the resale value of the commodity and has

Table 2.1.: Table of Experimental Design: Treatment structure.

Social Competition	**Number of participants: 240**	**Time Pressure**	
		Low time pressure [δ **= 1 MU,** τ **= 5.0 s**]	**High time pressure** [δ **= 1 MU,** τ **= 0.5 s**]
	No social competition [**computer opponents**]	NSC_LTP (48 participants)	NSC_HTP (48 participants)
	Social competition [**human opponents**]	SCO_LTP (72 participants)	SCO_HTP (72 participants)

Abbreviations: MU = Monetary units, s = Seconds, LTP = Low time pressure, HTP = High time pressure, NSC = No social competition, SCO = Social competition

to pay the price at which the second bidder dropped out of the auction. The resale value is the same for all three bidders in a single auction, but unknown ex ante. In all auctions, the resale value is determined from a uniform distribution with support on the discrete interval {46 MU, 95 MU} after the auction ends. The support of the value distribution is common knowledge, i.e., all bidders know the distribution and all bidders know that all other bidders know the distribution. However, bidders do not know the realized value until the auction has ended. We deliberately chose this setting because previous research has shown that bidders show strong physiological reactions when learning about a high private value prior to the auction start (Adam et al., 2011; Astor et al., 2013). Therefore, in order to isolate the effect of time pressure and social competition on physiological arousal and bidding behavior, we chose a setting in which all the bidders have an identical perception of their valuation before the auction starts. Moreover, in order to exclude that observed differences in bidding behavior are only driven by differences in the participants' individual risk preferences, we also control for this factor in the analysis. To this end, participants were asked to complete the risk aversion test by Holt and Laury (2002) after the sequence of auctions was completed. In the risk aversion test the participants have to decide consecutively between two lotteries with different levels of risk and expected payoffs. Based on how often a participant chooses the less risky lottery, the experimenter can approximate a participant's risk attitude. In this study, this measure is used to distinguish between participants that are risk averse (i.e., number of safe choices ≥ 5) and those that are not risk averse. And example of the risk aversion test as it was used in this lab experiment is shown in Appendix A.

2.3.2. Procedure

The experiment was conducted at Karlsruhe Institute of Technology, Germany. The experimental system was implemented using the z-Tree environment for lab experiments (Fischbacher, 2007). Altogether, 58 female and 182 male participants (240 in total, mean age = 22.09 years) participated in 40 sessions with 6 participants each. The participants were randomly recruited from a pool of undergraduate students with an academic background in economics. Before the experiment started, the participants were endowed with a lump sum payment of €15.00. The average final payment was €20.76, with €5.80 being the minimum payment and €38.20 the maximum.

Due to the physiological measurements, the actual experiment was preceded by a preparation phase in which the measurement electrodes were attached. Following the recommendations of Schmidt and Walach (2000), an initial five minute rest period was conducted during this preparation phase for calibration purposes. In order to allow the bidders' physiological arousal to return to a base value, an additional one minute rest period was introduced between two consecutive auctions. Before the experiment started, the participants were provided an instruction (an example of the instruction is shown in Appendix A) and they had to successfully complete a comprehension quiz as well as participate in a practice round in which gains and losses were not considered. Moreover, the interactions with the experimental system were limited to mouse inputs and the participants were equipped with earmuffs to avoid susceptibility to background noise.

During the experiment, we continuously measured the bidders' heart rate (HR) and skin conductance (SC) as proxies for their emotional processing. In particular, we recorded the electrical activity of the heart by means of electrocardiography (ECG) using a two-lead method with single-use electrodes placed on the left and right wrist. Each participant's HR was quantified throughout the experiment by measuring the time between successive R-waves in the ECG (Jennings et al., 1981). SC was recorded with a constant voltage 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 with standard electrodermal activity electrode paste (Boucsein, 1992; Dawson et al., 2007).

The sessions were conducted with an average room temperature of 22.52°C (72.54°F) and a relative humidity of 46.31%. These values are in accordance with the methodological recommendations of the Society for Psychophysiological Research (Fowles et al., 1981). The measurement of 16 participants failed due to technical issues with one measurement device. Moreover, the SC measurement results of 19 participants had to be removed from the data sample because their values were outside the range of the measurement system. The heart rate measurement results of 14 participants had to be removed from the data sample because of too much noise on the signal. Thus, the data set contains 205 measurements for SC and 210 for heart rate.

2.3.3. Physiological Measures

Hear rate (HR) and skin conductance (SC) reflect activity of the autonomous nervous system (ANS), which usually functions outside of conscious awareness and thus cannot directly be influence by free will (Andreassi, 2007).

HR is measured in beats per minute and provides insight into a participant's current level of arousal (Berntson et al., 2007). In the analysis, we specifically focus on the arousal that occurs towards the end of the auction, because previous research has shown that this phase receives most attention by the bidders. In particular, in this phase, bidders ultimately decide at which price they leave the auction and they are aware that decisions during this phase have irreversible consequences, i.e., determining winner, losers, and payments (Ariely and Simonson, 2003). Thus, the final phase of an auction is when auction fever should be the strongest and when the bidders' arousal might have an impact on their bids. Note that due to the natural respiratory sinus arrhythmia in HR, which is the periodic fluctuation in HR due to inhalation and exhalation, it is essential to average HR over a time period of several seconds (Hirsch and Bishop, 1981; Pollatos et al., 2007; Werner et al., 2009). In order to receive a valid proxy for arousal, thus, we average HR for each bidder during the last 15 seconds before a bidder leaves an auction. This point is determined individually for each bidder and each auction. Due to the between-subjects variability, every bidder's HR value was assessed relative to the individual basic arousal level that was measured during the initial rest period (θHR).

SC reflects activity of the sympathetic branch of the ANS. SC is measured in microsiemens (μS) and can be decomposed into tonic and phasic components. In order to analyze SC, the SC signal was decomposed into its tonic (SCL) and phasic (SCR.amp) components with the Ledalab analysis software (Benedek and Kaernbach, 2010). Similar to HR, the tonic component reflects the general arousal level of the examinee (skin conductance level, SCL), i.e., the ongoing current emotional state. Compared to HR, however, changes in SCL are rather inert and therefore not suitable for assessing arousal in the dynamic context of high time pressure auctions. The phasic component is denoted as the skin conductance response (SCR). SCRs are monophasic peaks and represent short bursts of sympathetic activity which are usually elicited by an external or internal stimulation. The amplitudes of SCRs, commonly denoted as SCR.amp, are proxies for the intensities of immediate emotions (Boucsein, 1992; Dawson et al., 2011). SCRs usually occur one to three seconds after the stimulus (Boucsein, 1992) which, in the case of this experiment, is the revelation of the auction outcome to the bidders. Therefore, only those amplitudes that are observed in that specific time frame are taken into account. Furthermore, amplitudes have to comply with a predefined amplitude criterion, i.e., amplitudes have to be greater or equal to 0.01 μS Fowles et al. (1981). In order to reduce the inherent left skewness and between-subjects variability, all SCR.amp values x are transformed $\log(x+1)$ and referenced to the activation in response to a neutral reference event, i.e., the notification that an auction starts soon (cf. Astor et al. (2013); Venables and Christie (1980)).

2.4. Results

2.4.1. Final Prices

Before we proceed to testing hypotheses, we first consider the impact of the treatments on final prices. Figure 2.2 shows that final prices are highest in high time pressure auctions with a social competition while the other three treatments yield similar final prices. A 2 (time pressure) $\times$ 2 (social competition) repeated measures (auction number #0-14) ANOVA confirms a significant effect of time pressure on final prices ($F(1, 1796) = 16.83$, $p < .001$), a significant effect of social competition ($F(1, 1796) = 17.17$, $p < .001$), and a significant interaction term time pressure $\times$ social competition ($F(1, 1796) = 7.52$, $p < .01$). In this analyses, we apply repeated measures ANOVAs whenever multiple observations per participant are recorded, e.g., in the analysis of final prices, bids, arousal, and immediate emotions. Pairwise comparisons using Bonferroni adjusted alpha levels confirm that final prices in the SCO_HTP treatment ($M = 70.53$ [$SD = 3.39$]) are significantly higher than in the SCO_LTP ($M = 68.51$ [$SD = 4.17$], $p < .001$), the NSC_HTP ($M = 68.68$ [$SD = 3.63$], $p < .001$), and the NSC_LTP ($M = 68.14$ [$SD = 3.43$], $p < .001$) treatment. Pairwise comparisons of the other treatments show no significant differences, except for a slight difference of 0.54 MU between the high time pressure and the low time pressure treatment in the no social competition condition ($p < .01$). This is intuitive as the computer opponents replicate the human bids from the corresponding social competition treatment. The effect of time pressure on final prices thus exists only in the social competition treatments, i.e., in auctions with a social competition. Moreover, there is indication for an increase in final prices across the set of 15 auctions ($F(14, 1796) = 5.43,\ p < .001$) as well as a marginally significant interaction of auction number × time pressure ($F(14, 1796) = 1.69,\ p < .10$). This time trend is analyzed in more detail in section 2.4.6.

Overall, the proportion of auctions won by human bidders is comparable across treatments. While by design a human bidder wins on average 33% of the auctions in the social competition treatments, 31% (35%) were won by human bidders in the NSC_HTP (NSC_NTP) treatment. Recall that bidders do not know the realization of the commodity ex ante. Before the end of the auction, bidders only know that the resale value will be randomly drawn after each auction from a discrete uniform distribution on the interval 46 MU, 95 MU. Thus, the expected resale value is 70.50 MU. The results show that final prices are not significantly different from the expected resale value of 70.50 MU in the SCO_HTP treatment ($M = 70.53$ [$SD = 3.39$], $t(359) = .156,\ p = .877$), but significantly below 70.50 MU in the SCO_LTP treatment ($M = 68.51$ [$SD = 4.17$], $t(359) = -9.048,\ p < .001$), NSC_HTP treatment ($M = 68.68$ [$SD = 3.63$], $t(719) = -13.428,\ p < .001$), and the NSC_LTP treatment ($M = 68.14$ [$SD = 3.43$], $t(719) = -18.483,\ p < .001$). This is remarkable, because participants are generally risk averse—as elicited with the risk aversion test by Holt and Laury (2002)—and should thus actually place bids well below the expected value in all treatments. Note, however, that differences in participants' payoffs are not significant across treatments, because the payoffs (unlike the final prices) are largely determined by the random draw of the common resale value and thus exhibit a higher variance. Recall

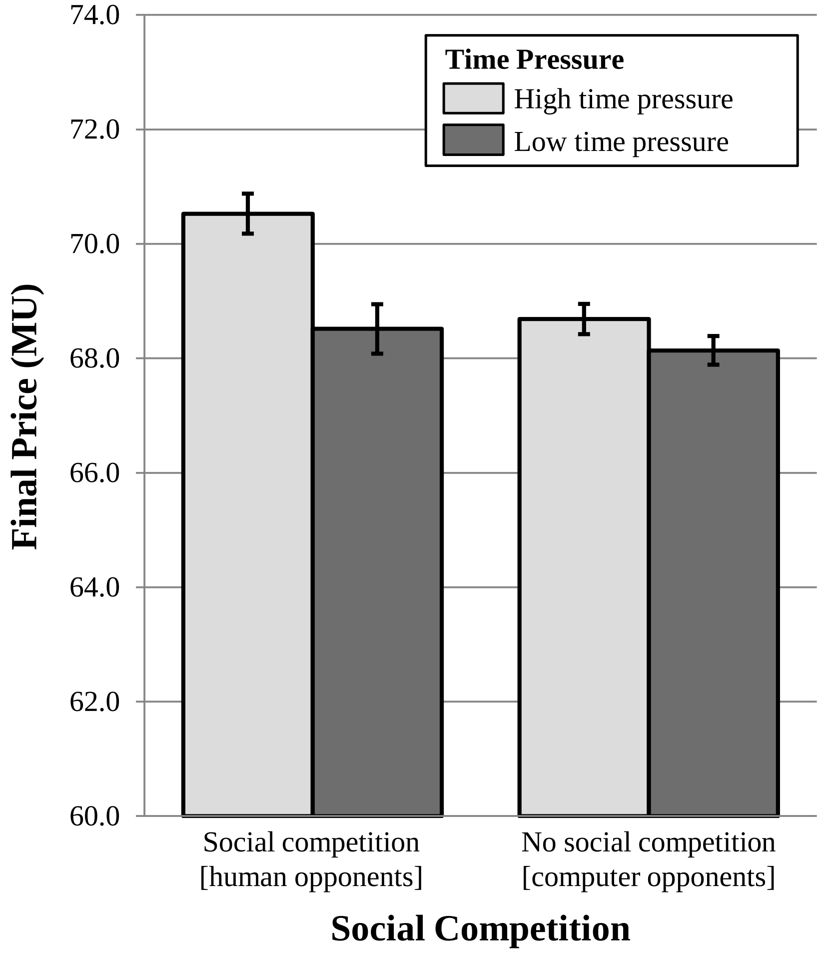


Figure 2.2.: Study Results: Final prices. Note: The error bars indicate the 95% confidence interval. Abbreviations: MU = Monetary units.

that the payoff of the winning bidder is computed as the difference between the random resale value and the final price.

2.4.2. The Effect of Time Pressure and Social Competition on Arousal

Figure 2.3 shows the average arousal level (θHR) for all bidders in the four treatments. Recall that, as outlined in the physiological measures section 2.3.3, because the final phase of an auction is particularly relevant for auction fever and because of the natural respiratory sinus arrhythmia in heart rate, θHR is assessed individually for each bidder based on the last 15 seconds before a bidder left an auction. Additional tests showed that the results also hold for other time windows as shown in section 2.4.6. As each participant took part in 15 auctions, we consider a 2 (time pressure) $\times$ 2 (social competition) repeated measures (auction number #0-14) ANOVA. In line with H1a, it confirms that the difference in θHR between the low time pressure (M = .986 [SD = .093]) and the high time pressure (M = 1.034 [SD = .087]) treatments is significant ($F(1, 2924) = 32.09,\ p < .001$). Moreover, and in line with H2a, also the difference in θHR between the no social competition (M = .997 [SD = .089]) and the social competition (M = 1.018 [SD = .095]) treatments is significant ($F(1, 2924) = 6.53,\ p < .05$). The interaction term time pressure $\times$ social competition is not significant ($F(1, 2924) = .07,\ p = .785$). In addition, and in line with previous physiological studies (Bradley et al., 1993; Glenn F. Wilson, 1992), we can observe that θHR mitigates across the set of 15 auctions ($F(14, 2924) = 35.74,\ p < .001$). This time trend is illustrated in section 2.4.6. In summary, we can conclude that time pressure (H1a) and social competition (H1b) have a positive influence on arousal.

2.4.3. The Effect of Time Pressure and Social Competition on Bids

In order to test the statistical significance of the impact of time pressure (H1b) and social competition (H2b) on bids, we consider the bid (i.e., the exit price) of each bidder in each of the 15 auctions. Note that the winner of the ascending clock auction is, by definition, the last bidder to stay in the auction. Thus, the bid (exit price) cannot be determined for the winning bidder. To be consistent in the analysis, we focus only on those participants for which also HR values were successfully obtained. As stated in the physiological measures section, heart rate (HR) values were successfully obtained for 210 participants. However, the results also hold when taking into account the bids of all 240 participants. Table 2.2 reports the regression results for direct and indirect effects of time pressure on bids. A 2 (time pressure) $\times$ 2 (social competition) repeated measures (auction number #0-14) ANOVA confirms a significant effect of time pressure ($F(1, 1880) = 10.79,\ p < .01$) and social competition ($F(1, 1880) = 4.18,\ p < .05$)

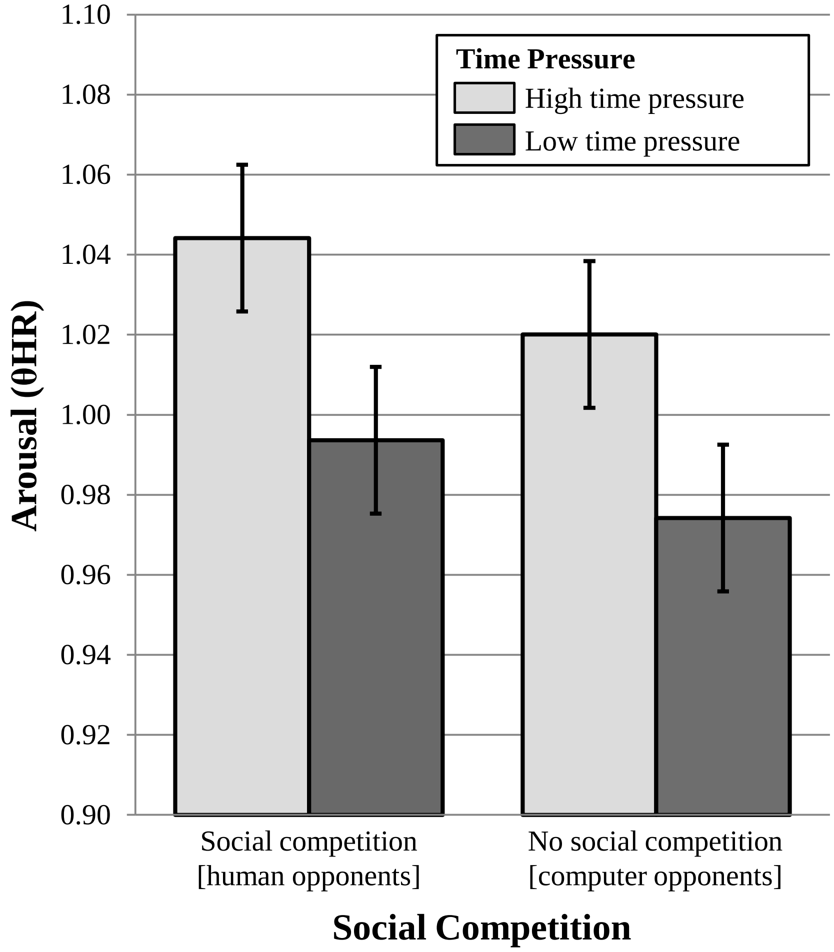


Figure 2.3.: Study Results: Arousal (θHR). Note: The error bars indicate the 95% confidence interval. Abbreviations: θHR = Normalized heart rate.

on bids. However, also the interaction term time pressure × social competition is significant ($F(1, 1880) = 18.30$, $p < .001$). Pairwise comparisons using Bonferroni adjusted alpha levels reveal that bids are significantly higher in the SCO_HTP treatment ($M = 69.09$ [$SD = 4.32$]) than they are in the SCO_LTP ($M = 64.48$ [$SD = 9.533$], $p < .001$), the NSC_HTP ($M = 64.88$ [$SD = 7.185$], $p < .001$), and NSC_LTP ($M = 66.09$ [$SD = 6.601$], $p < .001$). Pairwise comparisons of the other treatments show no significant differences, except for a slight difference between the SCO_LTP ($M = 64.48$ [$SD = 9.533$]) and the NSC_LTP ($M = 66.09$ [$SD = 6.601$], $p < .05$)

treatment, which might be explained by unusually low bids in the final auctions of the SCO_LTP treatment. Similar to final prices, there is indication for a time trend in bids across the set of 15 auctions ($F(14, 1880) = 1.72,\ p < .05$) as well as a significant interaction of auction number × time pressure ($F(14, 1880) = 2.45,\ p < .01$). This time trend is illustrated in section 2.4.6. In summary, we can conclude that in line with H1b time pressure has a positive influence on bids. This, however, only holds for auctions with a social competition.

2.4.4. The Mediating Role of Arousal on Bids

We now turn the focus to the relationship between a bidder's arousal and his or her bids. In the research model, we conjecture that in the presence of a social competition the effect of time pressure on bids is mediated by the bidders' arousal levels (H3). This relationship would be a clear indication of the existence of auction fever. In order to test this relationship, we conduct a mediation analysis according to the procedure described in Imai et al. (2010). We decided to use this mediation analysis approach, because it rests on less assumptions than traditional mediation approaches that rely on the linear structural equation model framework, like Baron and Kenny (1986), and because it can be employed for both linear models as well as nonlinear models. Thus, the approach by Imai et al. (2010) allows us to use a consistent and contemporary mediation analysis throughout the paper. We employed the package *medeff* by Hicks and Tingley (2011) to conduct the mediation analysis for this study in Stata 13. Robust standard errors clustered by participants were used to control for repeated measurements of the same participant.

The results of the mediation analysis are summarized separately for the social competition and the no social competition treatments in Table 2.2. Note that regression I and IV confirm the impact of time pressure on arousal (H1a). Regressions II and III (IV and V) test the direct and indirect effect of time pressure on bids for the social competition (no social competition) treatments. For the social competition treatments, the mediation analysis confirms a significant total effect ($TE = 4.848,\ SE = .993,\ LL = 2.882,\ UL = 6.812$), as well as a significant direct effect ($DE = 4.095,\ SE = .906,\ LL = 2.310,\ UL = 5.862$), and a significant indirect effect ($IE = .756,\ SE = .303,\ LL = .239,\ UL = 1.427$), where LL and UL refer to the lower and upper limits of the 95% confidence interval. Since zero is not in the 95%

confidence interval, the indirect effect is significantly different from zero at $p < .05$ (two-tailed). It is important to highlight, however, that in line with H3 this only holds for the social competition treatments. For the no social competition treatments, neither the total effect ($TE = -1.229,\ SE = 1.027,\ LL = -3.271,\ UL = .812$), the direct effect ($DE = -1.296,\ SE = 1.048,\ LL = -3.360,\ UL = .747$), nor the indirect effect ($IE = .064,\ SE = .199,\ LL = -.310,\ UL = .470$) are significant. In summary, we can reject the null hypotheses in favor of the research hypotheses H3. Arousal as measured by θHR, partially mediates the effect of time pressure on bids when bidders compete with human opponents. A robustness check for this mediation analysis is provided section 2.4.6.

2.4.5. Immediate Emotions in Response to Auction Outcome

Finally, we investigate the bidders' immediate emotions in response to winning and losing an auction. The bidders' normalized SCR.amp values in response to seeing the auction outcome are depicted in Figure 2.4. The bar chart indicates that the event of winning an ascending clock auction induces a stronger immediate emotion than the event of losing the auction.

In order to test hypothesis H4, we conduct a 2 (time pressure) $\times$ 2 (social competition) $\times$ 2 (auction outcome) repeated measures (auction number #0-14) ANOVA. The analysis confirms that in line with H4, the difference in SCR.amp between the response to winning the auction ($M = 2.081$ [$SD = 2.157$]) and the response to losing the auction ($M = .848$ [$SD = 1.275$]) is significant ($F(1, 2678) = 96.92,\ p < .001$). Moreover, when comparing the low time pressure treatment ($M = 1.470$ [$SD = 1.627$]) with the high time pressure treatment ($M = 1.021$ [$SD = 1.789$]), one can observe that the intensity of immediate emotions is significantly lower when time pressure is high ($F(1, 2678) = 11.36,\ p < .001$). By contrast, the analysis does neither reveal a significant influence of social competition on SCR.amp ($F(1, 2678) = 1.94,\ p = .164$), nor a significant interaction term time pressure $\times$ social competition ($F(1, 2678) = .18,\ p = .669$). Finally, in line with previous studies (Astor et al., 2014; Bradley et al., 1993), physiological responses mitigate over the course of 15 auctions ($F(14, 2678) = 2.74,\ p < .001$).

Table 2.2.: Regression results for direct and indirect effects.

	Dependent Variables					
	Social Competition			**No Social Competition**		
Independent Variables	**(I) Arousal (ΘHR)**	**(II) Bid**	**(III) Bid**	**(IV) Arousal (ΘHR)**	**(V) Bid**	**(VI) Bid**
Dummy: high time pressure	.058*** (.011)	4.848*** (.993)	4.107*** (.907)	.048*** (.014)	-1.229 (1.027)	-1.282 (1.049)
Dummy: risk averse	-.003 (.010)	.277 (.978)	.321 (.949)	.012 (.016)	.554 (1.152)	.541 (1.141)
Dummy: female	-.011 (.010)	-1.109 (1.121)	-.972 (1.078)	.032* (.015)	-1.589 (1.226)	-1.624 (1.225)
Auction number (0-14)	-.006*** (.001)	-.007 (.070)	.074 (.064)	-.004*** (.001)	.071 (.068)	.075 (.071)
Arousal (ΘHR)			12.730** (4.345)			1.107 (3.750)
Constant	1.032*** (.011)	64.550*** (.902)	51.410*** (4.781)	.991*** (.017)	65.570*** (1.076)	64.47*** (4.012)
	N = 1276 R^2 = .182	N = 1276 R^2 = .091	N = 1276 R^2 = .109	N = 870 R^2 = .143	N = 870 R^2 = .020	N = 870 R^2 = .020

$^+$ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Note. Regression coefficients with robust standard errors clustered by participant in parentheses. Abbreviations: ΘHR = Normalized heart rate.

Effects of time pressure on bids with arousal as the mediator.	**Social Competition**				**No Social Competition**			
	Mean	**SE**	**95% Confidence Interval Lower (LL)**	**Upper (UL)**	**Mean**	**SE**	**95% Confidence Interval Lower (LL)**	**Upper (UL)**
Total effect (TE)	4.848	.993	2.882	6.812	-1.229	1.027	-3.271	.812
Direct effect (DE)	4.095	.906	2.310	5.862	-1.296	1.048	-3.360	.747
Indirect effect (IE)	.756	.303	.239	1.427	.064	.199	-.310	.470

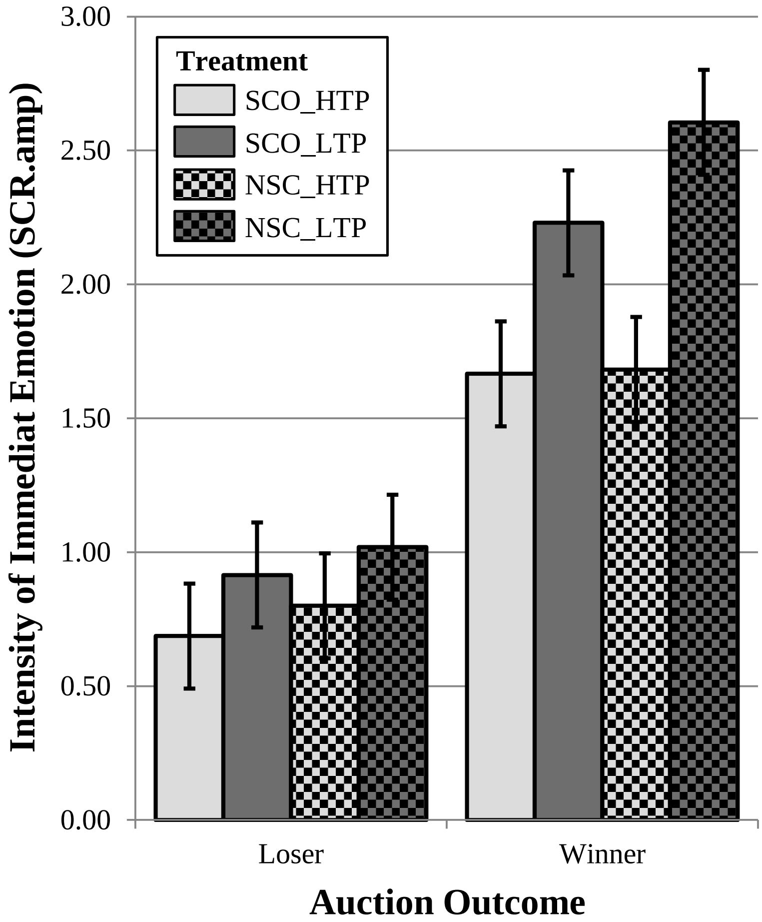


Figure 2.4.: Study Results: Immediate emotions (SCR.amp) in response to auction outcome. Note: The error bars indicate the 95% confidence interval. Abbreviations: SCO = Social competition, NSC = No social competition, HTP = High time pressure, LTP = Low time pressure, SCR.amp = Skin conductance response amplitude.

2.4.6. Supplementary Robustness Analyses

Time Trends for Arousal, Final Prices, and Bids

Figure 2.5, 2.6, and 2.7 illustrate time trends for arousal, final prices, and bids for this study. In line with previous studies (Glenn F. Wilson, 1992; Bradley et al., 1993), Figure 2.5 shows a decrease of arousal over time. This is intuitive as participants sit in front of a computer screen and thus there is less effort needed for bodily movements.

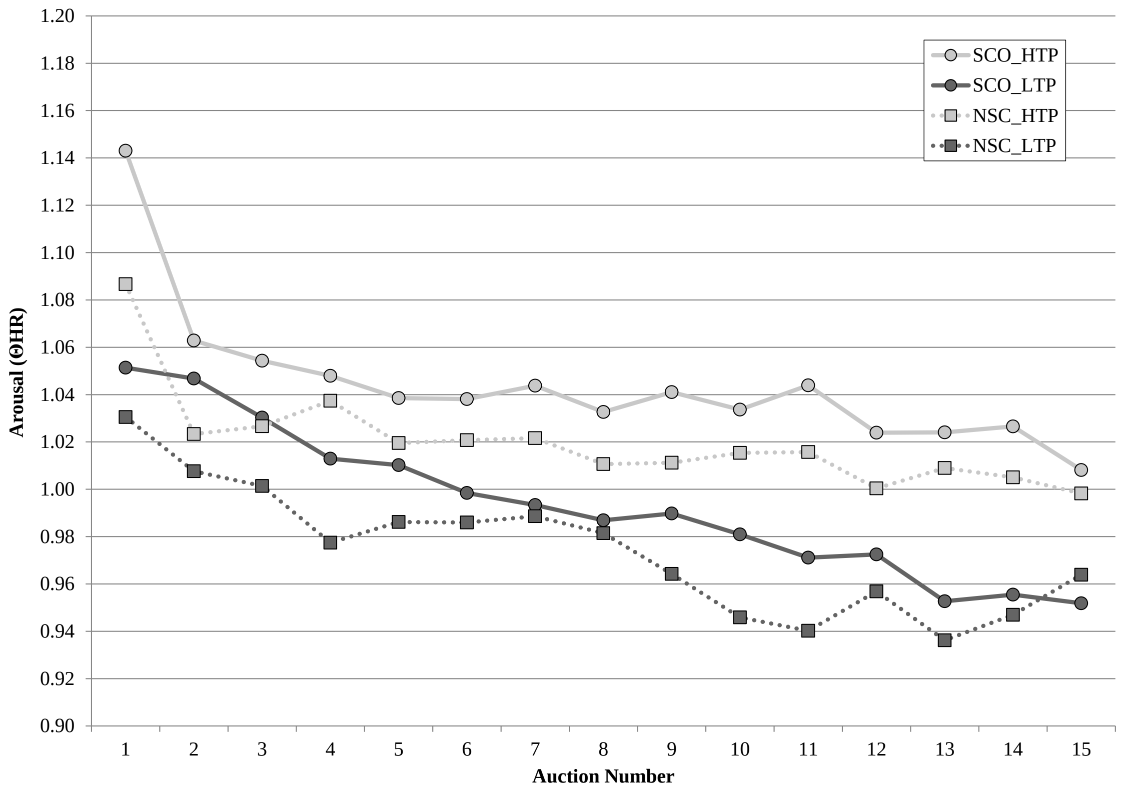


Figure 2.5.: Arousal by treatment. Abbreviations: SCO = Social competition, NSC = No social competition, HTP = High time pressure, LTP = Low time pressure, θHR = Normalized heart rate.

As for final prices (Figure 2.6), we can observe a slight increase in final prices over time. In the following, orthogonal polynomial contrasts were used to further analyze these trends. We find both, a significant linear ($F(1, 1796) = 23.32, p < .001$) and quadratic time trend ($F(1, 1796) = 23.18, p < .001$), but an insignificant cubic trend. As suggested by Figure 2.6, this indicates that prices tend to increase initially but decrease again in later auctions. Table 2.3 provides the corresponding tests for time trends in final prices for each treatment. Notably, it is found that the social competition and high time pressure (SCO_HTP) treatment is the only treatment for which no quadratic or cubic time trend was found. Here, we find only a significant linear trend ($F(1, 1796) = 12.98, p < .001$), which indicates that final prices rise from auction to auction and do not decline in later auctions. This complements the previous analysis, where it is concluded that the effect of auction fever is only visible in this treatment.

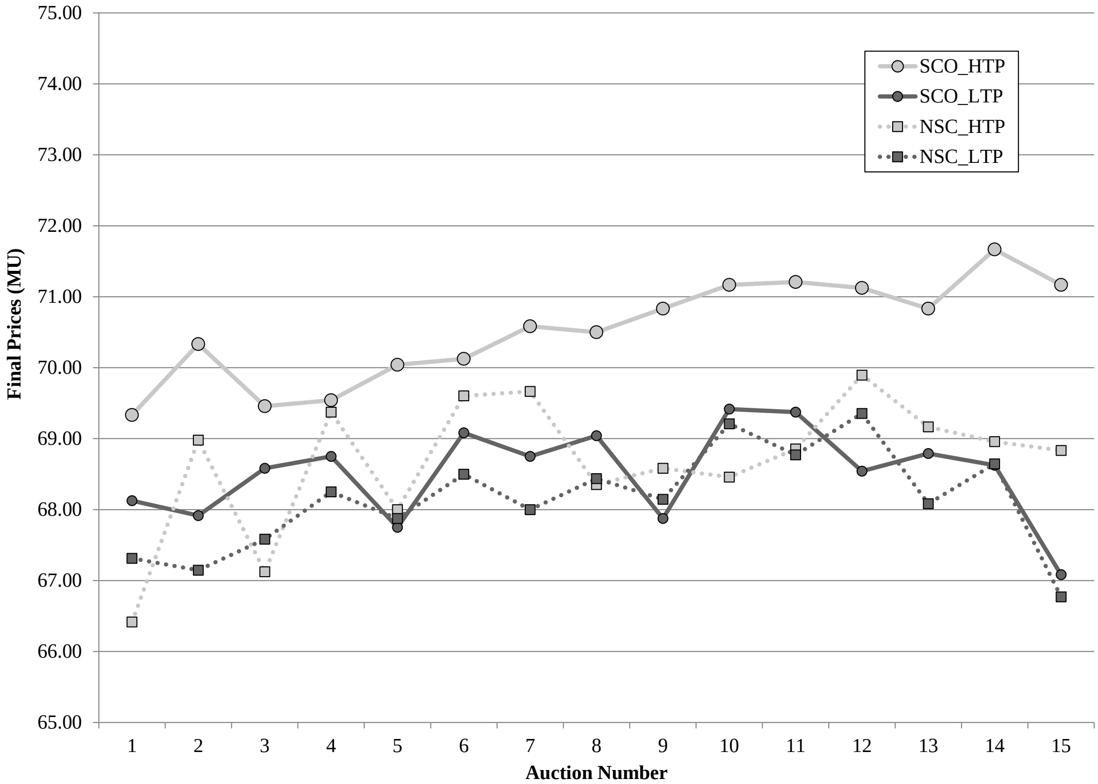


Figure 2.6.: Final prices by treatment. Abbreviations: SCO = Social competition, NSC = No social competition, HTP = High time pressure, LTP = Low time pressure, MU = Monetary units.

Next, time trends in bids are analyzed. Note that this analysis includes the bids of all participants, as opposed to the analysis of final prices, which only includes the winning bids. Therefore, the bids show more variance than the final prices, which, expectedly, yields less significant time trends. Using orthogonal polynomial contrasts, we find an insignificant linear, a significant quadratic trend ($F(1, 1880) = 7.62, p < .01$), and insignificant higher order trends. As suggested by Figure 2.7, the separate analysis of orthogonal polynomial contrasts within each treatment condition (cf. Table 2.4) show that, again, the social competition and high time pressure (SCO_HTP) treatment is the only treatment with a positive significant linear trend ($F(1, 1880) = 10.34, p < .001$) and insignificant higher order trends. The other treatments show no or negative time trends, which could be attributed to the absence of auction fever in these treatments.

Table 2.3.: Within-subjects contrasts of *auction number* within each treatment for the final price analysis.

Treatment	**Contrast**	***df***	***F***	**Sig.**
Social Competition and High Time Pressure (SCO_HTP)	Linear	1	12.98	<.001***
	Quadratic	1	.02	.901
	Cubic	1	.14	.704
Social Competition and Low Time Pressure (SCO_LTP)	Linear	1	.05	.817
	Quadratic	1	4.61	.032*
	Cubic	1	.84	.359
No Social Competition and High Time Pressure (NSC_HTP)	Linear	1	12.14	<.001***
	Quadratic	1	9.54	.002**
	Cubic	1	3.10	.078^{+}
No Social Competition and Low Time Pressure (NSC_LTP)	Linear	1	4.79	.029*
	Quadratic	1	13.65	<.001***
	Cubic	1	4.11	.043*

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

Table 2.4.: Within-subjects contrasts of *auction number* within each treatment for the bids analysis.

Treatment	**Contrast**	***df***	***F***	**Sig.**
Social Competition and High Time Pressure (SCO_HTP)	Linear	1	10.34	.001**
	Quadratic	1	1.32	.251
	Cubic	1	.01	.934
Social Competition and Low Time Pressure (SCO_LTP)	Linear	1	9.64	.002**
	Quadratic	1	2.14	.143
	Cubic	1	3.83	.050^{+}
No Social Competition and High Time Pressure (NSC_HTP)	Linear	1	.16	.692
	Quadratic	1	.41	.520
	Cubic	1	1.89	.170
No Social Competition and Low Time Pressure (NSC_LTP)	Linear	1	4.01	.045*
	Quadratic	1	5.65	.018*
	Cubic	1	3.85	.050^{+}

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

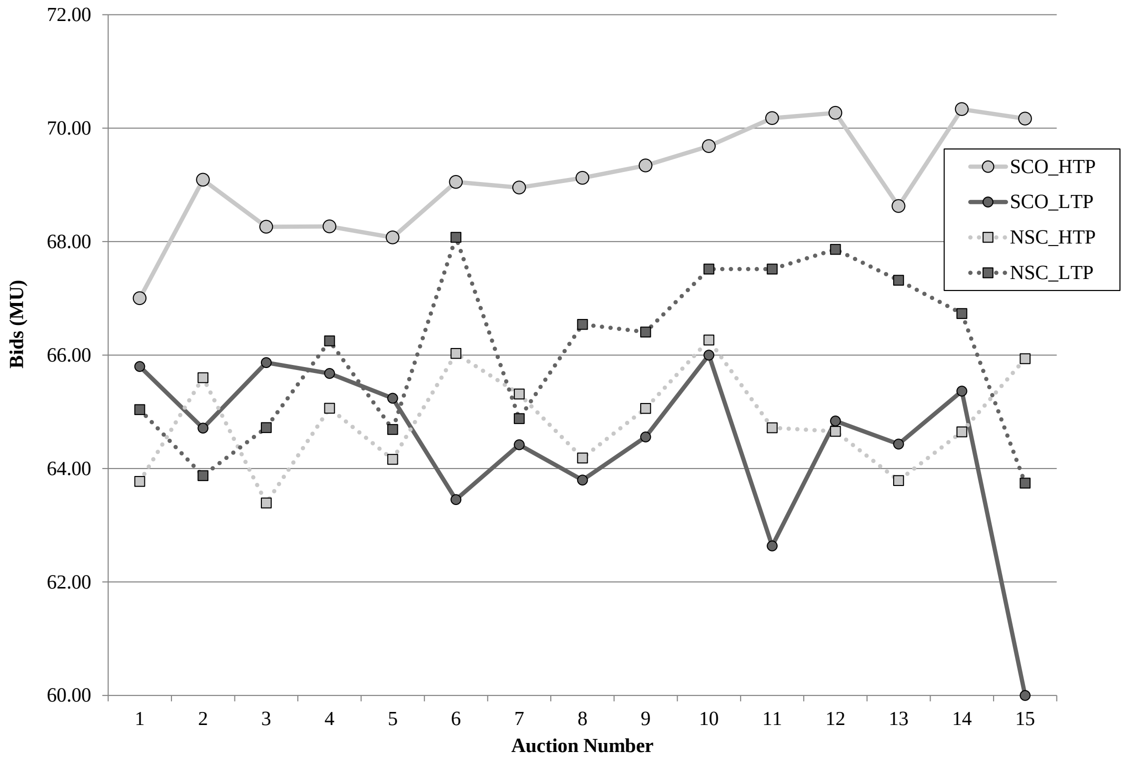


Figure 2.7.: Bids by treatment. Abbreviations: SCO = Social competition, NSC = No social competition, HTP = High time pressure, LTP = Low time pressure, MU = Monetary units.

Time Windows Analysis for Arousal

In the following, we calculate the arousal parameter θHR for different time intervals and number of price steps. Based on these values, we conduct a set of repeated measures (auction number #0-14) ANOVAs. As can be seen in Table 2.5 and Table 2.6, the results for time pressure and social competition are consistent across different time intervals and different number of price steps.

Analysis for Participants with Heart Rate and Skin Conductance Data

As a robustness check, we conduct a mediation analysis that considers only those participants with valid skin conductance and heart rate measurements (N=181). The results are summarized in Table 2.7 and are consistent with the results listed in Table 2.2.

Table 2.5.: Repeated measures ANOVA for arousal with different time intervals.

Independent variables	Arousal (ΘHR) for Different Time Intervals					
	(I) 10 Seconds		**(II) 15 Seconds**		**(III) 20 Seconds**	
	***F* value**	**Sig.**	***F* value**	**Sig.**	***F* value**	**Sig.**
Dummy: high time pressure	30.60	<.001***	31.81	<.001***	38.05	<.001***
Dummy: no social competition	7.09	.008**	6.01	.015*	5.47	.020*
Dummy: risk averse	.10	.747	.03	.853	.03	.874
Dummy: female	.56	.456	.21	.649	.03	.852
Auction number (0-14)	35.90	<.001***	35.74	<.001***	38.10	<.001***
	N = 3148		N = 3148		N = 3148	
	R^2 = .564		R^2 = .567		R^2 = .581	

$^+$ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Table 2.6.: Repeated measures ANOVA for arousal with different time intervals.

	Arousal (ΘHR) for Different Time Intervals					
Independent variables	**(I) Last 3 Price Steps**		**(II) Last 4 Price Steps**		**(III) Last 5 Price Steps**	
	***F* value**	**Sig.**	***F* value**	**Sig.**	***F* value**	**Sig.**
Dummy: high time pressure	9.69	.002**	11.88	<.001***	14.24	<.001***
Dummy: no social competition	7.61	.006**	7.38	.007**	7.21	.008**
Dummy: risk averse	.05	.824	.05	.815	.05	.831
Dummy: female	.75	.387	.74	.391	.65	.422
Auction number (0-14)	33.26	<.001***	34.30	<.001***	35.07	<.001***
	N = 3148		N = 3148		N = 3148	
	R^2 = .537		R^2 = .542		R^2 = .549	

$^+$ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Table 2.7.: Supplementary regression results for direct and indirect effects for participants with HR and SC ata.

	Dependent Variables					
	Social Competition			No Social Competition		
Independent Variables	(I) Arousal (ΘHR)	(II) Bid	(III) Bid	(IV) Arousal (ΘHR)	(V) Bid	(VI) Bid
Dummy: high time pressure	.074*** (.010)	5.163*** (1.135)	4.118*** (1.014)	.044** (.014)	-1.810 (1.109)	-1.844 (1.125)
Dummy: risk averse	.001 (.010)	.474 (1.106)	.453 (1.081)	.012 (.017)	.814 (1.210)	.804 (1.200)
Dummy: female	-.015 (.010)	-.993 (1.218)	-.785 (1.193)	.035* (.016)	-1.823 (1.226)	-1.850 (1.226)
Auction number (0-14)	-.007*** (.001)	-.010 (.082)	.086 (.075)	-.004*** (.001)	.056 (.074)	.059 (.076)
Arousal (ΘHR)			14.071** (4.524)			.763 (3.840)
Constant	1.025*** (.010)	64.355*** (.993)	49.930*** (4.979)	.990*** (.017)	65.515*** (1.107)	64.759*** (4.093)
	N = 1072, $R^2 = .251$	N = 1072, $R^2 = .098$	N = 1072, $R^2 = .117$	N = 794, $R^2 = .144$	N = 794, $R^2 = .030$	N = 794, $R^2 = .030$

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

Note. Regression coefficients with robust standard errors clustered by participant in parentheses.

Effects of time pressure on bids with arousal as the mediator.	Social Competition				No Social Competition			
	Mean	SE	95% Confidence Interval Lower (LL)	Upper (UL)	Mean	SE	95% Confidence Interval Lower (LL)	Upper (UL)
Total effect (TE)	5.163	1.135	2.913	7.414	-1.810	1.109	-4.019	.399
Direct effect (DE)	4.105	1.013	2.109	6.080	-1.859	1.123	-4.072	.332
Indirect effect (IE)	1.064	.387	.382	1.899	.045	.190	-.312	.433

Supplementary Regression Analysis

In order to test the robustness of the regression results, we complementarily conduct a set of random-effects regressions grouped by participant. The results are summarized in Table 2.8 and are consistent with the results listed in Table 2.2.

2.5. Discussion

Internet auctions are believed to elicit high levels of arousal in the bidders, which can eventually culminate in auction fever. We showed that physiological measurements can be used the show a positive relation of physiological arousal and its impact on bidding behavior in electronic auctions—and therefore the existence of auction fever. However, to robustly conclude that physiological arousal in the context of social competition is the true drivers of auction fever in electronic auctions, we must further investigate other possible drivers. Only then, we can derive managerial or theoretical implications.

To analyze further possible drivers of auction fever, we need to investigate psychometric aspects, such as joy of winning, fear of losing, or fun of competing, as well as alternative explanations, such as cognitive load. The next chapter will address these aspects in addition to manipulation checks of the existing treatment structure (i.e., variation of the degree and implementation of time pressure and social competition).

Therefore, an exhaustive discussion is postponed for now but it is provided in Section 3.5. Section 3.5 combines the results of Chapter 2 and Chapter 3 and addresses the discussion of both chapters in detail.

2.6. Conclusion

In this chapter, we investigated the role of physiological arousal and its impact on bidding behavior in electronic auctions. To this end, we conducted a laboratory experiment with physiological measurements in order to systematically investigate the existence of the auction fever phenomenon and its drivers under controlled conditions. In the experiment, bidders participated in ascending clock auctions with either high or low time pressure. In order to investigate the moderating role of social competition, bidders either competed with human opponents or with computer opponents. Based on the results, we can empirically (i.e., using physiological measurements) establish a positive

Table 2.8.: Supplementary regression results for direct and indirect effects using random-effects regressions grouped by participant.

	Dependent Variables					
	Social Competition			No Social Competition		
Independent Variables	**(I) Arousal (ΘHR)**	**(II) Bid**	**(III) Bid**	**(IV) Arousal (ΘHR)**	**(V) Bid**	**(VI) Bid**
Dummy: high time pressure	.056*	4.389***	4.101***	.041**	-1.058	-1.072
	(.011)	(.895)	(.882)	(.014)	(.993)	(1.006)
Dummy: risk averse	-.004	.466	.483	.010	.766	.764
	(.011)	(.867)	(.843)	(.014)	(1.055)	(1.062)
Dummy: female	-.011	-.970	-.911	.028+	-.676	-.683
	(.013)	(1.027)	(.999)	(.016)	(1.189)	(1.199)
Auction number (0-14)	-.007***	.001	.035	-.005***	.069	.070
	(<.001)	(.038)	(.042)	(<.001)	(.044)	(.047)
Arousal (ΘHR)			5.278*			.343
			(.487)			(3.007)
Constant	1.038***	65.156***	59.670***	.998***	65.681***	65.340***
	(.010)	(.791)	(2.694)	(.014)	(1.030)	(3.173)
	N = 1276	N = 1276	N = 1276	N = 870	N = 870	N = 870
	R^2 = .181	R^2 = .091	R^2 = .104	R^2 = .141	R^2 = .017	R^2 = .017

$^+$ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Note. Generalized least squares regressions grouped by participant. Regression coefficients with standard errors in parentheses.

relationship between time pressure, social competition, bidders' arousal, and bidding behavior.

Using physiological measurements as an objective measure of arousal, the results show that in ascending clock auctions the bidders experience a higher degree of physiological arousal when time pressure is high and when bidders are competing with human opponents rather than with computer opponents. With respect to bidding behavior, we have shown that the bidders place higher bids when time pressure is high and that this effect is partially mediated by arousal. This result provides physiological evidence of the existence of auction fever. Moreover, we find that auction fever is no longer observable when bidders compete with computer opponents rather than with human opponents: both the direct and the indirect effect of time pressure on bids are not significant when bidders compete with computer opponents. Summarizing, the social competition among human bidders is a necessary prerequisite for the auction fever phenomenon and can thus be seen as its true driver. Further, with respect to the immediate emotions that are induced by seeing the auction outcome, we find that winning an ascending clock auction is experienced significantly more intensely than losing. In other words, the joy of winning is experienced stronger than the frustration of losing.

Chapter 3.

Competitive Arousal and Bidding Behavior in Ascending Auctions

In this chapter, we refine the investigation of the role of arousal and its impact on bidding behavior in electronic auctions. In contrast the the previous investigation of physiological arousal, we now turn our focus to competitive arousal perceived in the social competition. We measure competitive arousal also in a controlled lab environment, identical to the previous lab experiment, using psychometric scales of self-report questionnaires. To increase the robustness of our finding, we investigate alternative explanations for arousal, such as cognitive, and we conduct manipulation checks of the the treatment structure. Thus, this chapter investigates Research Question 2, which states:

> **Research Question 2:** *How is competitive arousal perceived in the social competition of ascending auctions and what is its impact on bidding?*

3.1. Introduction

In this chapter, we seek to provide further insight into what are the actual drivers of bidders' arousal, clarify the existence of the auction fever phenomenon, and their influences on bidding behavior. To this end, we investigate auction fever by employing a second controlled lab experiment, which builds on the experiment presented in Chapter 2. In this lab experiment, bidders' arousal is assessed with subjective measures, i.e., using psychometric scales via self-report questionnaires. Thereby, we again focus specifically on time pressure and the inherent social competition of auctions, as these factors are considered to be the main drivers for so-called competitive arousal (Ku et al., 2005; Malhotra, 2010). However, we modify the parameters for time presser and social competition as manipulation check for the previous experiment. As the lab experiment in this chapter builds on the experiment of the previous chapter, in this experiment, we also conduct ascending clock auctions in which the standing price increases at fixed time intervals (i.e., English clock auction or Japanese auction (Milgrom and Weber, 1982)). Bidders' again interact with the auction by dropping out of the auction at their desired prices, which is possible at each bidding increment. The auction ends when only one bidder remains in the auction. This bidder acquires the commodity for the standing price at which the last but one bidder left the auction.

With this chapter, we confirm the four contribution state in Chapter 2 and we add an additional fifth contribution. By using the self-report data, we can reveal that bidders' arousal is mainly driven by perceived competition. This shows, that auction fever exits in ascending electronic auction, but only in auctions where bidders face a social competition.

3.2. Theoretical Background and Hypotheses

We continue with the research hypotheses that were introduced in Chapter 2. However, we now focus on a better understanding the drivers of the increase in arousal and the bidders' emotional processes in auctions. Thus, the research hypotheses, as previously introduced, remain unaltered. Therefore, they state:

> **Hypothesis 1 (H1):** *Under the influence of higher time pressure levels, bidders (a) experience more arousal and (b) place higher bids in ascending clock auctions.*
>
> **Hypothesis 2 (H2):** *Under the influence of higher social competition levels, bidders (a) experience more arousal and (b) place higher bids in ascending clock auctions.*
>
> **Hypothesis 3 (H3):** *In the presence of a social competition, arousal mediates the effect of time pressure on bids.*
>
> **Hypothesis 4 (H4):** *Winning an ascending clock auction induces a stronger immediate emotion in the bidders than losing an ascending clock auction.*

However, as a complement to the physiological measurements in Chapter 2, we now use psychometric scales in this study to individually measure several constructs that have been linked to emotional bidding in previous research. In particular, we measure desire to win (DTW), fear of losing (FOL), and competitive arousal (CAR). Thereby, the items used to measure CAR focus on arousal, feeling competitive, and fun of competing. These constructs, which we identified from the extant literature (cf. Section 3.3.3), were adapted for the present context, pretested, and validated with respect to discriminant and convergent validity. Moreover, we assess the bidders' joy of winning and frustration of losing in response to the auction outcome. As for alternative explanations, such as cognitive load, we use the NASA TLX (task load index) to assess the bidders during bidding. By using a common value auction, we control that all bidders have the same information on the true value of the good, i.e., the probability distribution of the common value.

3.3. Experimental Design

This study is meant to complement the insights gained from the study presented in Chapter 2. Therefore, we also conduct a controlled lab experiments in an identical lab environment and only treatment-specific changes in the experimental design. The experiment was conducted at Karlsruhe Institute of Technology (KIT), Germany. Study participants were randomly recruited from a pool of undergraduate students with an academic background in economics by using ORSEE (Greiner, 2004). The study constitutes a 2 (time pressure) × 2 (social competition) between-subjects factorial design and includes four treatments (cf. Table 3.1). Before the experiment started, the participants were again provided an instruction (an example of the instruction is shown in Appendix B) and they had to successfully complete a comprehension quiz as well as participate in a practice round in which gains and losses were not considered. Moreover, the interactions with the experimental system is limited to mouse inputs and the participants are equipped with earmuffs to avoid susceptibility to background noise. During the experiments, participants take on the role of a bidder in a series of ascending clock auctions. We have deliberately chosen this auction format, because (i) it enables us to maintain a high level of experimental control in the lab and (ii) this format has strong similarities to the English auction, the proxy auction used on eBay, and the penny auction, which

Table 3.1.: Table of Experimental Design: Treatment structure.

Number of participants: 216		**Time Pressure**	
		No time pressure [δ = **5 MU**, $\tau \geq$ **25.0 s**]	**Medium time pressure** [δ = **5 MU**, τ = **5.0 s**]
Social Competition	**Social competition** [**human opponents**]	SCO_NTP (54 participants)	SCO_MTP (54 participants)
	Increased social competition [**human opponents with nicknames and avatars**]	ISC_NTP (54 participants)	ISC_MTP (54 participants)

Abbreviations: MU = Monetary units, s = Seconds, NTP = No time pressure, NTP = No time pressure, MTP = Medium time pressure, SCP = Social Competition, ISC = Increased social competition

is frequently used on entertainment auction platforms. All decision making during the experiment is directly related to real monetary payoffs (Smith, 1976), i.e., each participant has to individually accumulate so-called monetary units (MU), which are converted into real money and paid out in cash after the experiment. In the experiment, 1 MU is equivalent to €0.20 and each participant is endowed with an initial lump sum payment of €15.00.

In comparison to the study reported in Chapter 2, in study, we focus on the case of human opponents only and use psychometric scales to assess the bidders' perceptions of arousal and immediate emotions. Moreover, we use longer time intervals in order to test the robustness of the results and systematically change bidders' graphical representation on the screen to further manipulate the social competition among bidders.

An auction is finished as soon as at least two of the three bidders decide to drop out of the auction. The winning bidder receives the resale value of the commodity and has to pay the price at which the second bidder dropped out of the auction. The resale value is the same for all three bidders in a single auction, but unknown ex ante. In all auctions, the resale value is drawn from a discrete uniform distribution on the interval {110 MU, 155 MU}. The value distribution is common knowledge, i.e., all bidders know the distribution and all bidders know that all other bidders know the distribution. However, bidders do not know the resale value until the auction has ended.

We have deliberately chosen this setting, because previous research has shown that bidders show strong physiological reactions when learning about a high private value prior to the auction start (Adam et al., 2011; Astor et al., 2013). Therefore, in order to isolate the effect of time pressure and social competition on arousal and bids, we have chosen a setting in which all the bidders have an identical perception of their valuation before the auction starts. Moreover, in order to exclude that observed differences in bids are only driven by differences in the participants' individual risk preferences, we also control for risk attitudes in the analysis. To this end, participants were asked to complete the risk aversion test by Holt and Laury (2002) after the sequence of auctions was completed. In the risk aversion test, the participants have to decide consecutively between two lotteries with different levels of risk and expected payoffs. Based on how often a participant chooses the less risky lottery, the experimenter can approximate a participant's risk attitude. As in the previous study, we use this measure to distinguish between participants that are risk averse (i.e., number of less risky choices ≥ 5) and those that are not risk averse. Therefore, the used questionnaire is identically to the one used in the study in Chapter 2. An example of the questionnaire is shown in Appendix A.

3.3.1. Treatment Structure

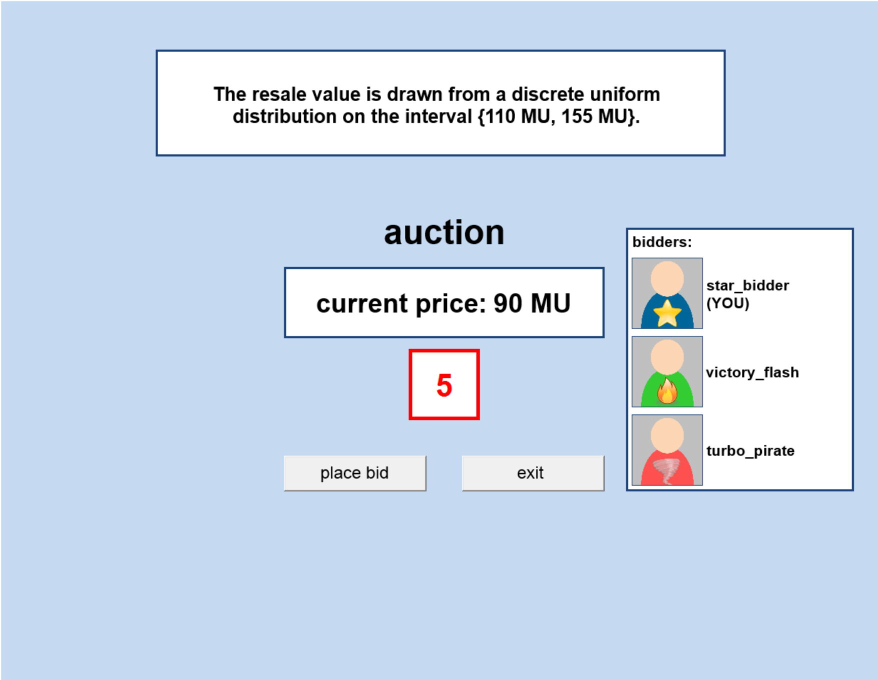
To complement the insights gained from the previous study (cf. Chapter 2), this study differs in several aspects. First, we use psychometric scales in this study to assess arousal in order to provide further insight into the actual drivers of arousal. Second, we introduce longer time intervals for investigating time pressure in order to test the robustness of the results from the previous study. Third, we increase the bidding increment δ from 1 MU to 5 MU and run a sequence of only 4 auctions per participant. This is done in order to accommodate the longer time intervals. Otherwise the duration of the experiment would have been exceedingly long and results could have been compromised due to participants' fatigue. The initial price p_{min} is set at 90 MU. Fourth, bidders have to actively click the "place bid" button in order to stay in the auction. Thereby, we exclude the possibility that participants only stayed longer in the auction, because they were not able to click the "exit" button in time. In case all remaining bidders choose to exit the auction at the same time, one of the remaining bidders is randomly selected as the winner of the auction. Fifth, we focus on the case of human opponents only and systematically change the bidders' graphical representation in order to manipulate the social competition among human bidders.

With respect to time pressure, we consider a medium time pressure (MTP) condition, in which the current standing price is increased by δ=5 MU every τ=5.0 seconds, and a no time pressure (NTP) condition, where the time interval is set to $\tau \geq$25.0 seconds. In the no time pressure condition, bidders need to wait at least 25 seconds before the next price step is reached, but can also take more time than 25 seconds. With respect to social competition, we consider a social competition (SCO) condition and an increased social competition (ISC) condition. The social competition condition is identical to that of the previous study in Chapter 2, i.e., bidders know that there are two other human bidders in the auction but there is no further information displayed on the screen. By contrast, the increased social competition condition aims at increasing the level of social competition among the bidders by displaying nicknames and avatars of the three bidders in an auction. Figure 3.1 shows two screenshots (translated to English) of auctions with increased social competition (Figure 3.1 a) and with social competition (Figure 3.1 b). Both screenshots show auctions with medium time pressure as indicated by the remaining auction time in the middle of the screen. Nicknames were generated full factorial from a list of nine objects and nine names. Each bidder was then presented 9 unique object-name combinations as nicknames and 9 matching avatars to choose from. Nicknames and avatars could be selected independently from each other, i.e., a bidder could choose an avatar that did not match with the nickname. All in all, this procedure ensured that bidders could reasonably self-select their combination of nickname and avatar while it avoided to introduce any systematic bias and guaranteed for all bidders to have a unique nickname and a unique avatar during the experiment.

Using avatars mimics what is done by the Internet auction sites, such as *dealdash.com* and *madbid.com*. As a manipulation check for the influence of displaying nicknames and avatars on social competition, we included a question at the end of the experiment to which participants responded on an eleven-point Likert scale (“I perceived the other participants as competitors”; 1 = “Strongly Disagree”; 11 = “Strongly Agree”).

3.3.2. Procedure

The study was implemented in Java using the experimental platform *Brownie* (Hariharan et al., 2015; Müller et al., 2014). Altogether, 52 female and 164 male participants (216 in total, mean age = 21.98 years) participated in 24 sessions with 9 participants each.



(a) ISC_MTP treatment

(b) SCO_MTP treatment

Figure 3.1.: (a): Screenshot of an auction with increased social competition and medium time pressure (ISC_MTP treatment). (b): Screenshot of an auction with social competition and medium time pressure (SCO_MTP treatment).

The average final payment was € 17.86 (min=€ 10.60, max=€ 24.65). In order to equate the length of sessions across treatments, the rest period between consecutive auctions was one minute in the no time pressure sessions and four minutes in the medium time pressure sessions, respectively.

3.3.3. Instrument Development

While the previous study in Chapter 2 focused on objective measurements of arousal only, this study assesses the bidders' perceptions in order to provide further insight into the actual drivers of arousal. Based on the literature, we identified three concrete constructs that are related to emotional processes in auctions and have been linked to bidding. First, bidders can experience a desire to win an auction (Cheema et al., 2012; Malhotra, 2010). Second, bidders can experience a fear of losing an auction (Delgado et al., 2008). Third, bidders can experience competitive arousal, which stems from the thrill of beating competitors (Ku et al., 2005).

The development of instruments for these three constructs was based on procedures described in Churchill Jr. (1979) and DeVellis (2011). We reviewed the extant literature to identify validated questions for the constructs or to generate new constructs for which no validated constructs existed. With respect to the desire to win construct, we developed a construct with three question items, which are based on Cheema et al. (2012) and Malhotra (2010). The fear of losing construct was developed in analogy with the desire to win construct with a specific focus on losing. Finally, the (competitive) arousal construct was developed on the basis of three question items of which one item is based on Malhotra (2010) while the other two refer to the bidders' general arousal level and the thrill of bidding against other bidders.

All questions were anchored on an eleven-point Likert scale. Feedback was obtained from several information systems and marketing faculty members in order to assess the constructs' conceptual validity and content validity, based upon which changes were made to some items. The revised items were pilot-tested with 72 students.

Table 3.2 provides an overview of the constructs and question items that were used in the final survey as well as their validity and stability. For discriminant validity, an exploratory principal factor analysis with promax rotation was conducted and Horn's parallel analysis was performed to extract the factors. Parallel analysis is widely accepted to be one of the most accurate factor extraction methods (Hayton et al., 2004). In particular, it outperforms the Guttmann-Kaiser eigenvalue greater than one rule (Glorfeld, 1995). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is with 0.845 "meritorious," which confirms that the data is suitable for factor analysis. All items load properly towards the respective constructs and have only little cross-loading. Convergent validity, i.e., the degree to which the questions items measuring the same construct agree, was assessed using Cronbach's alpha. All constructs well exceed the threshold of 0.70 suggested by Peterson (1994). Therefore, the constructs used appear to have adequate discriminant and convergent validity.

Table 3.2.: Validity and stability of the measurement constructs and question items.

Item	**Cronbach's Alpha**	**Factor**		
		1	**2**	**3**
CAR1: I was aroused during the auction.	.905	-.041	.020	**.893**
CAR2: It was fun to bid against the other bidders.		.050	-.013	**.819**
CAR3: I felt competitive during the auction.		.046	.002	**.832**
DTW1: I really wanted to win the auction.	.936	**.828**	.086	.025
DTW2: It was important to me to win the auction.		**.810**	.113	.006
DTW3: It was important to me to win against the other bidders.		**.786**	.145	.056
FOL1: I really did not want to lose the auction.	.932	.035	**.873**	.010
FOL2: It was important to me to not lose the auction.		.041	**.884**	-.011
FOL3: It was important to me to not lose against the other bidders.		.149	**.783**	.013
Eigenvalue		5.149	1.497	.462

Note. CAR = (Competitive) Arousal, DTW = Desire to Win, FOL = Fear of Losing (All question items were translated from their original version).

In addition to assessing constructs that are assumed to reflect emotional processes, we also assess the NASA Task Load Index as a workload measure for covering bidders' cognitive demand (Hart and Staveland, 1988). However, due to the experimental design of this study, where participants sit in front of a computer screen during the entire session, we excluded the category "physical demand" as it is not relevant in this context.

3.4. Results

3.4.1. Manipulation Check for the Increased Social Competition Condition

The results of the manipulation check, as described above, show that participants in the increased social competition condition reported a higher degree of agreement ($M = 7.843$ [$SD = 2.859$]) to the statement that they perceived the other bidders as competitors than did participants in the social competition condition ($M = 6.324$ [$SD = 2.682$], $F(1, 212) = 16.18$, $p < .001$). Significant influences of time pressure were not observed ($F(1, 212) = 1.39$, $p = .240$). The interaction term time pressure $\times$ social competition is not significant ($F(1, 212) = .19$, $p = .659$). Taken together, this indicates that the increased social competition manipulation was successful.

3.4.2. Final Prices

Figure 3.2 indicates that time pressure and social competition have a positive influence on final prices. A 2 (time pressure) $\times$ 2 (social competition) repeated measures (auction number #0-3) ANOVA confirms that final prices are higher in the medium time pressure ($M = 131.63$ [$SD = 3.175$]) than in the no time pressure ($M = 130.313$ [$SD = 2.849$]) treatments ($F(1, 119) = 12.07$, $p < .001$). Moreover, also the difference in final prices between the social competition ($M = 130.59$ [$SD = 2.742$]) and the increased social competition ($M = 131.35$ [$SD = 3.356$]) treatments is significant ($F(1, 119) = 4.04$, $p < .05$). By contrast, neither the interaction term time pressure $\times$ social competition ($F(1, 119) = .001$, $p = .999$) nor a time trend over the course of the auctions ($F(1, 119) = .25$, $p = .864$) are significant. Thus, when bidders compete with other human bidders, time pressure and also the level of the social competition both significantly impact final prices. Similar to the previous study in Chapter 2, differences in the participants' payoffs are not significant.

3.4.3. The Effect of Time Pressure and Social Competition on Arousal

In the analysis, we first focus on the perceptual questions used to measure the constructs on arousal, desire to win, and fear of losing. Figure 3.3 shows the average level of arousal for all bidders in the four treatments. In line with H1a, a 2 (time pressure) $\times$ 2 (social competition) ANOVA confirms that the difference in arousal between the no time pressure ($M = 4.753$ [$SD = 2.103$]) and the medium time pressure ($M = 7.062$ [$SD = 1.904$]) treatments is significant ($F(1, 212) = 74.31,\ p < .001$). Moreover, and in line with H2a, also the difference in arousal between the social competition ($M = 5.485$ [$SD = 2.249$]) and the increased social competition ($M = 6.330$ [$SD = 2.306$]) treatments is significant ($F(1, 212) = 9.97,\ p < .01$). The interaction term time pressure $\times$ social competition is not significant ($F(1, 212) = .39,\ p = .534$).

With respect to workload (as measured by means of the NASA Task Load Index), we can observe a marginally significant difference between the no time pressure ($M = 3.841$ [$SD = 1.575$]) and the medium time pressure ($M = 4.252$ [$SD = 1.614$]) treatments ($F(1, 212) = 3.57,\ p = .060$), while social competition does not have a significant influence on workload ($F(1, 212) = .07,\ p = .799$). Moreover, neither the treatment variable time pressure nor the treatment variable social competition influence the constructs desire to win and fear of losing significantly. In summary, we can conclude that in line with H1a and H2b time pressure and social competition significantly increase arousal, while desire to win and fear of losing are not affected. This is also confirmed by regression I in Table 3.3. We will return to the relationship between all four constructs (i.e., arousal, desire to win, fear of losing, and workload) when analyzing the mediating role of arousal (H3).

3.4.4. The Effect of Time Pressure and Social Competition on Bids

In order to test the statistical significance of the impact of time pressure (H1b) and social competition (H2b) on bids, we assess whether bidders do or do not place a bid of 135 MU or more, i.e., whether bidders are willing to accept a price above the expected value of 132.5 MU. This approach differs from the analysis of Chapter 2, because the price increments in the previous study are much coarser than in this study (5 MU vs. 1 MU)

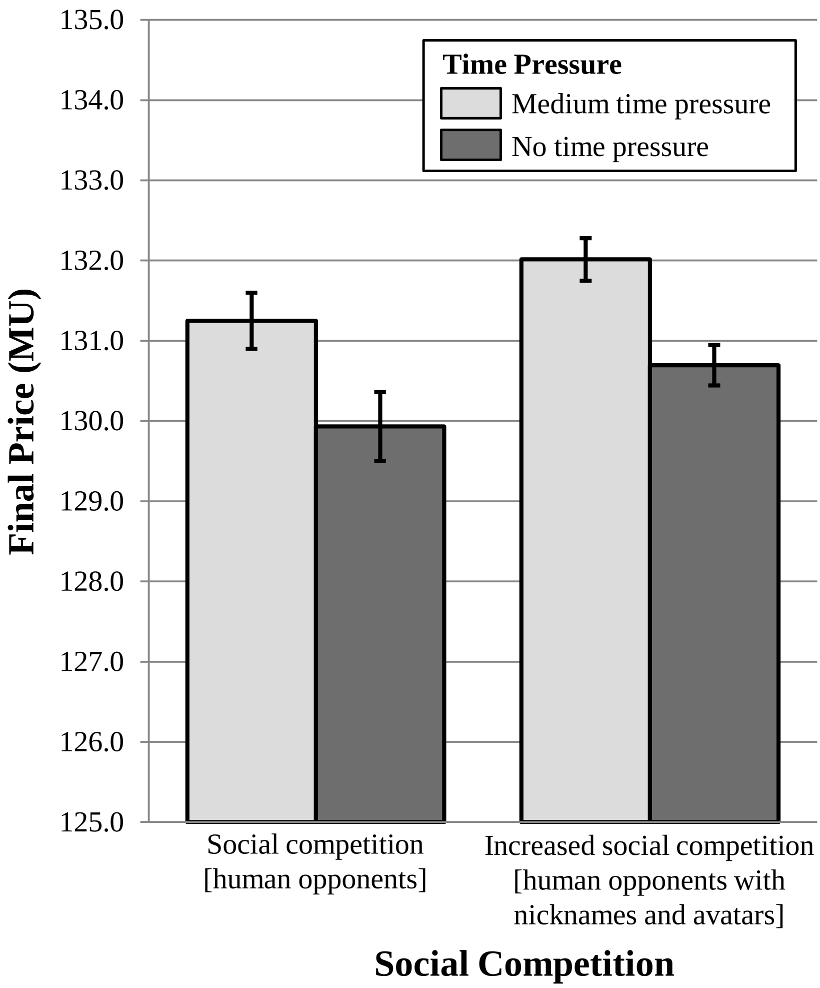


Figure 3.2.: Study Results: Final prices. Note: The error bars indicate the 95% confidence interval. Abbreviations: MU = monetary units.

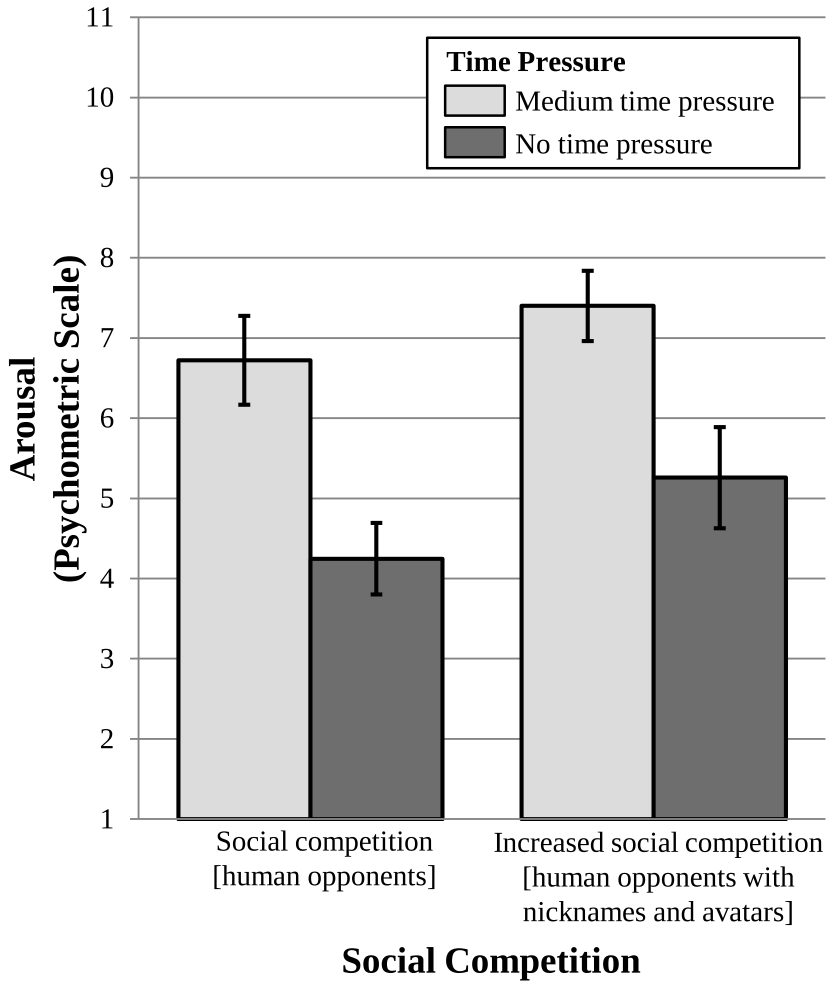


Figure 3.3.: Study Results: Arousal. Note: The error bars indicate the 95% confidence interval.

Table 3.3.: Regression results for direct and indirect effects.

	Dependent Variables		
Independent Variables	**(I) Arousal**	**(II) Bid ≥ 135**	**(III) Bid ≥ 135**
Dummy: medium time pressure	2.244***	.639*	.130
	(.219)	(.274)	(.374)
Dummy. increased social competition	.815***	.525*	.273
	(.219)	(.261)	(.274)
Dummy: risk averse	.348	-.408^{+}	-.509*
	(.225)	(.247)	(.256)
Dummy: female	-.223	.069	.136
	(.258)	(.279)	(.283)
Desire to win	.471***	.296***	.187*
	(.062)	(.072)	(.091)
Fear of losing	-.013	-.072	-.058
	(.064)	(.076)	(.070)
Workload	.105	.071	.064
	(.072)	(.084)	(.080)
Auction number (0-3)		.005	.005
		(.095)	(.096)
Arousal			.257*
			(.108)
Constant	1.372***	-4.105***	-4.794***
	(.387)	(.616)	(.707)
	N = 216	N = 864	N = 864
	R^2 = .536	Pseudo-R^2=.111	Pseudo-R^2=.138

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

Note: Regression coefficients with standard errors in parentheses. Specifications II and III are based on logit regressions with robust standard errors clustered by participant. The Pseudo-R^2 values are based on Nagelkerke's R^2. The factors *arousal*, *desire to win* and *fear of losing* are based on question items. The factor *workload* was assessed based on the NASA Task Load Index (Hart and Staveland, 1988).

for reasons given above. Table 3.1 reports the regression results for direct and indirect effects of time pressure on bids. In line with hypotheses H1b and H2b, regression II confirms a significant influence of time pressure ($b = .649,\ SE = .279,\ z = 2.335,\ p < .001$) and a marginally significant influence of social competition ($b = 1.683,\ SE = .451,\ z = 1.941,\ p = .052$) on the probability to place a bid of 135 MU or more. Moreover, risk averse bidders exhibit a marginally significant tendency to place lower bids ($b = -.478,\ SE = .264,\ z = -1.807,\ p = .071$). Significant influences of gender and auction number are not observed. In summary, the results are in line with the previous study and we can conclude that H1b and H2b are supported, i.e., bidders place higher bids under higher levels of time pressure and social competition.

3.4.5. The Mediating Role of Arousal on Bids

Similar to the study in Chapter 2, we conduct a mediation analysis according to the procedure described in Imai et al. (2010) in order to test the mediating role of arousal on bids. The results are summarized in Table 3.1. In line with H3, the mediation analysis confirms a significant total effect ($TE = .065,\ SE = .025,\ LL = .015,\ UL = .112$) and a significant indirect effect ($IE = .053,\ SE = .024,\ LL = .009,\ UL = .102$) of time pressure on bids. By contrast, the direct effect is not significant ($DE = .012,\ SE = .033,\ LL = -.056,\ UL = .074$), indicating that the effect of time pressure on bids is fully mediated by arousal.

Furthermore, the perception data assessed in this study allows us to exclude desire to win, fear of losing, and workload as possible mediators for the impact of time pressure on bids. First, as we have seen from the results for H1a and H2a, neither desire to win nor fear of losing were significantly affected by time pressure, which excludes these factors as possible mediators. Second, even though workload is marginally influenced by time pressure, the regression analysis in Table 3.1 does not reveal a significant effect of workload on bids (see regression II and III in Table 3.1). This excludes workload as a possible mediator.

Finally, the analysis in Table 3.1 reveals a direct effect of desire to win on bids, which is partially mediated by arousal. In particular, as can be seen in regression I, there is a significant impact of desire to win on arousal ($b = .471,\ SE = .065,\ t = 7.200,\ p < .001$). Furthermore, as can be seen in regression III, there is a significant impact of desire to win on bids ($b = .187,\ SE = .091,\ t = 7.200,\ p < .05$). As shown in Table 3.4, a mediation analysis of desire to win via arousal on bids reveals a significant total effect (TE = .0077, SE = .0012, LL = .0052, UL = .0100), a significant indirect effect (IE = .0033, SE = .0021, LL = .0005, UL = .0086), and a significant direct effect (DE = .0044, SE = .0018, LL = .0004, UL = .0077). Thus, even though the desire to win can be excluded as a mediator, this factor is nevertheless an important element in auctions with a social competition. By contrast, significant influences of fear of losing and workload on arousal and bids were not observed.

Table 3.4.: Mediation analyses direct and indirect effects.

Effects of time pressure on bids with arousal as the mediator.	**Mean**	**SE**	**95% Confidence Interval**	
			Lower (LL)	**Upper (UL)**
Total effect (TE)	.065	.025	.015	.112
Direct effect (DE)	.012	.033	-.056	.074
Indirect effect (IE)	.053	.024	.009	.102

Effects of desire to win on bids with arousal as the mediator.	**Mean**	**SE**	**95% Confidence Interval**	
			Lower (LL)	**Upper (UL)**
Total effect (TE)	.0077	.0012	.0052	.0100
Direct effect (DE)	.0044	.0018	.0004	.0077
Indirect effect (IE)	.0033	.0021	.0005	.0086

3.4.6. Immediate Emotions in Response to Auction Outcome

With respect to the bidders' immediate emotions in response to the auction outcome, participants indicated to what extent they experienced a joy in response to winning ("I experienced joy when I won an auction.") and a frustration in response to losing ("I experienced frustration when I lost an auction.") on an eleven-point scale (1="Strongly Disagree"; 11="Strongly Agree"). These values are used to assess the intensity of immediate emotions in response to different auction outcomes (winner or loser). The results are summarized in Figure 3.4.

In order to test hypothesis H4, we conduct a 2 (time pressure) × 2 (social competition) × 2 (auction outcome) ANOVA with repeated measures on the auction outcome. In line with H4, the analysis confirms the immediate emotions in response to winning (M =

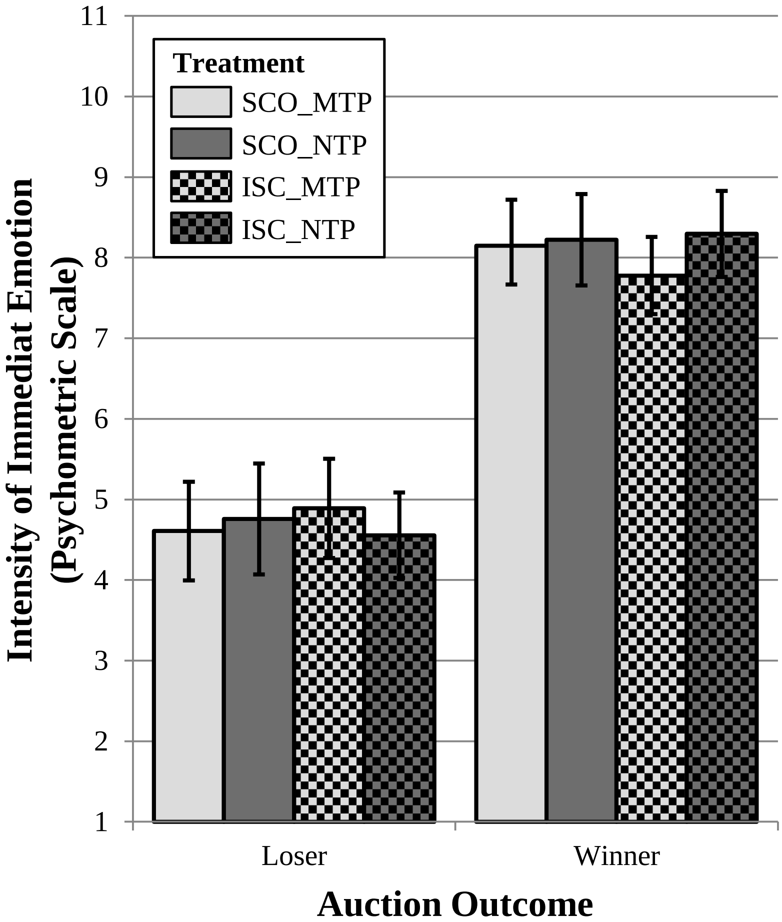


Figure 3.4.: Study Results: Immediate emotions in response to auction outcome. Note: The error bars indicate the 95% confidence interval. Abbreviations: SCO = social competition, ISC = increased social competition, MTP = medium time pressure, NTP = notime pressure.

8.111 [$SD = 2.018$]) are significantly stronger than the immediate emotions in response to losing ($M = 4.704$ [$SD = 2.285$], $F(1, 215) = 360.38$, $p < .001$). By contrast, neither time pressure ($F(1, 215) = .19$, $p = .663$) nor social competition ($F(1, 215) = .06$, $p = .812$) significantly affect the intensity of immediate emotions. This is in contrast to the previous study in Chapter 2, where we observed that immediate emotions were weaker in auctions with higher time pressure. While this difference is not the focus of this investigation, it may be due to the differences in the degree of time pressure between the two studies.

3.4.7. Supplementary Robustness Analyses

In order to test the robustness of our results, we complementarily conduct a set of random-effects logit regressions grouped by participant. The results are summarized in Table 3.5 and are consistent with the results listed in Table 3.3.

3.5. Discussion

3.5.1. Summary of Results and Theoretical Implications

As stated before, Internet auctions are believed to elicit high levels of arousal in the bidders, which can eventually culminate in auction fever. Whether or not auction fever really exists, however, has been frequently questioned, since there are also a number of alternative explanations for why bidders place unexpectedly high bids in online retail auctions—e.g., transaction and search costs, trust towards a platform, and bounded rationality (Carare and Rothkopf, 2005; Malmendier and Lee, 2011; Park et al., 2012). As it is notoriously hard to show in field studies that auction fever is actually one of the reasons for higher bids, two lab experiments were conducted in order to investigate the existence of the auction fever phenomenon and its drivers under controlled conditions. These studies are unique in the sense that they investigate the emergence of auction fever in ascending auctions while considering (i) objective and subjective assessments of bidders' arousal through physiological measurements (study Chapter 2) and psychometric scales (study Chapter 3), (ii) the interaction of time pressure and social competition on arousal and bids, and (iii) the intensity of bidders' immediate emotions in response to winning and losing an auction.

Table 3.5.: Supplementary regression results for direct and indirect effects using random-effects logit regressions grouped by participant.

	Dependent Variables		
Independent Variables	**(I) Arousal**	**(II) Bid ≥ 135**	**(III) Bid ≥ 135**
Dummy: medium time pressure	2.244***	.780*	.183
	(.219)	(.313)	(.355)
Dummy. increased social competition	.815***	.624*	.333
	(.219)	(.305)	(.308)
Dummy: risk averse	.348	-.411	-.530$^+$
	(.225)	(.308)	(.303)
Dummy: female	-.223	.101	.208
	(.258)	(.347)	(.338)
Desire to win	.471***	.350***	.231*
	(.062)	(.097)	(.099)
Fear of losing	-.013	-.088	-.082
	(.064)	(.091)	(.088)
Workload	.105	.082	.075
	(.072)	(.095)	(.092)
Auction number (0-3)		.006	.006
		(.107)	(.106)
Arousal			.279**
			(.093)
Constant	1.372***	-4.918***	-5.465***
	(.387)	(.770)	(.807)
	N = 216	N = 864	N = 864
	R^2 = .536	Pseudo-R^2=.165	Pseudo-R^2=.212

$^+$ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Note. Regression coefficients with standard errors in parentheses. Specifications II and III are based on random-effects logit regressions grouped by participant. The Pseudo-R^2 values are based on McKelvey & Zavoina's R^2. The factors *arousal*, *desire to win* and *fear of losing* are based on question items (cf. section 3.3.3). The factor *workload* was assessed based on the NASA Task Load Index (Hart and Staveland, 1988).

The results show that both time pressure (H1) and social competition (H2) have a systematic influence on arousal and bids. Compared to the base line, where bidders participate anonymously against other human bidders, bids and arousal can (i) either be increased by de-anonymizing bidders (here, in the second study, through nicknames and avatars), or (ii) be decreased by substituting the human opponents with computer opponents (first study). Moreover, arousal is not a mere by-product of behavior, but in the presence of a social competition acts as mediator for the impact of time pressure on bids. Thus, we find empirical evidence that auction fever really exists—but only when bidders are engaged in a social competition (H3). By contrast, when the bidders compete with computer opponents, auction fever is no longer observable in this study. In particular, even though we observe that also bidders who compete with computer opponents experience higher arousal levels in auctions with higher time pressure, this arousal does not translate into higher bids.

From a theoretical perspective, this result indicates that in the absence of a social competition the bidders rely more on their cognitive processes when placing their bids and less on their affective processes. In “dual system” models of human decision making, the complex interplay between cognitive and affective processes is usually simplified by distinguishing between an analytic cognitive system and an emotionally charged affective system (Lee, Amir, and Ariely, 2009), which—depending on the situation—each can play a dominant role in determining human behavior (Ariely and Loewenstein, 2006). While this conceptualization is necessarily an oversimplification of the human mind, the distinction of scenarios in which either the role of cognition or affect is more pronounced has “substantial value in explaining a wide variety of human behavior“ (Lee, Amir, and Ariely, 2009, p.174). For the case of online retail auctions, the study shows that affective processes have a definite influence on human decision making when bidders compete with human opponents. This can be seen in the significant mediating effect of arousal on bids in the social competition and increased social competition treatments. In this sense, arousal needs a focus in order to culminate in auction fever, and this focus stems from the social competition of bidding against human opponents. By contrast, this focus seems to be missing in auctions without a social competition; possibly due to the lack of opportunity to obtain social status (van den Bos, Talwar, and McClure, 2013; van den Bos, Golka, Effelsberg, and McClure, 2013). In this scenario, the role of affective processes in determining bidding behavior is less pronounced. In fact, as can be seen in the no social competition treatment, the study reveals that in absence of a social competition arousal has no significant influence on bids, which is in line with results of previous research in the context of bargaining showing that humans behave less impulsive when interacting with computer opponents (Rilling et al., 2004; Sanfey et al., 2003). Taken as a whole, this means that the social competition among human bidders is a necessary prerequisite for the auction fever phenomenon and can thus be seen as its true driver. Moreover, we find that it is particularly the "desire to win" (and not, for example, the "fear of losing") that fuels bidders' arousal in the context of a social competition. In this sense, it is not enough to win, others must lose! The bidders need to feel the urge to beat other human bidders, otherwise arousal does not flash over to behavior. Finally, we could even show that auction fever can be stimulated by fueling the social competition through the use of nicknames and avatars.

The results also provide further insight into the more general revenue equivalence controversy dating back to Vickrey (1961). The revenue equivalence theorem states that under specific assumptions the first-price sealed-bid, the second-price sealed-bid, the descending clock (Dutch), and the ascending clock (English) auction yield on average the same revenue. However, several empirical studies have shown that the revenues in dynamic auctions differ significantly from the revenues in the corresponding sealed-bid auctions, which has been attributed to the real-time element inherent to dynamic auctions (Ariely and Simonson, 2003; Cox et al., 1982; Katok and Kwasnica, 2008). The results of the two conducted lab experiments support this reasoning, but in addition highlight that also the element of social competition is crucial, as we observe no difference in bids between low and high time pressure auctions when the bidders compete with computer opponents. Moreover, the results also show that, with respect to the real-time element, the ascending auction and the descending auction differ in a systematic way: In a descending auction, each bidder is at any given point, at which the auction is still running, in control over stopping the auction and winning it with certainty ("click-to-win") (Adam et al., 2012). By contrast, in an ascending auction a bidder has only control over actively dropping out and losing the auction with certainty ("click-to-lose"). Thus, the only way arousal can translate into more risk taking is placing lower bids in the descending auction and placing higher bids in the ascending auction, respectively. This is exactly what we observe in these studies.

This systematic difference between the two auction formats also becomes evident in the emotions experienced by the bidders in response to learning about the auction outcome. In particular, the results show that the joy of winning an ascending auction is experienced significantly more intensely than the frustration of losing it (H4), while Adam et al. (2012) found the opposite pattern in the descending auction. This difference between the two auction formats is intuitive, because in the descending auction losing comes as a surprise, whereas in the ascending auction it is winning that comes as a surprise. When bidders decide to drop out of an ascending auction, they have accepted the inevitability of losing the auction. By contrast, when bidders decide to stay in the auction, they literally yearns for all the other bidders to drop out of the auction before they do. As a result, the joy of winning is particularly pronounced in the ascending auction.

3.5.2. Managerial Implications

Online auction sites have control over a multitude of parameters that affect the design and format of the auction and thus the shopping experience. This is an important distinction between online auctions and static fixed price offers, on the one hand, as well as offline auctions, on the other hand, which are much more limited in this respect. In an online environment, where competition is just one click away, emotions and arousal can be understood as a quality characteristic of Internet auctions (Childers et al., 2001; Lee et al., 2009; Stern and Stafford, 2006), attracting especially hedonic consumers, who "love to shop because they enjoy the shopping process" (To et al., 2007, p.775). Thus, if online marketplaces want to continue to be successful in the future, it will be increasingly important for them to differentiate themselves from competitors by offering consumers an exciting shopping experience. The research results highlight that specific parameters can be used to make shopping more exciting by affecting the consumers' emotions and that this in turn has an impact on final prices.

In particular, the results show that auctioneers should focus specifically on ascending auctions, as these auctions inherently pronounce the "joy of winning" and thus convey a more enjoyable shopping experience to bidders than descending auctions. Already during the auction process, bidders can experience a strong desire to win the auction, which in turn fuels arousal and bids. Arousal plays a key role in this dynamic process: Driven by the social nature of auctions, bidders feel competitive and experience fun to bid against other bidders. By increasing time pressure and social competition, the auctioneer can further heat up this competitive arousal and enkindle auction fever. Taken as a whole, this results in a more exciting shopping experience and higher revenues. The results show, however, that arousal only translates into higher bids in the presence of a social competition. When bidders do not compete with other human bidders, their arousal is lower and auction fever is no longer observable. Auction retail sites that aim at inducing auction fever should thus highlight the presence of other human bidders on their site, while non-social bidding sites should be aware that increasing arousal levels alone is not sufficient for generating higher revenues.

As investigated in the two lab experiments, the auction's clock speed is one possible design parameter for inducing time pressure. Further options are, for instance, highlighting the remaining time or introducing an "auction time" that runs faster than real-time. As for social competition, the results show that the social competition among bidders can be increased by displaying nicknames and avatars of the bidders on the auction screen. Other elements that leverage social facilitation and put bidders in the spotlight are highlighting the current highest bidder, displaying competitive messages (Malhotra, 2010), or priming bidders with a thrill of competition (Cheema et al., 2012). In 2007, for example, a prominent eBay advertisement campaign used the slogan, "It's better when you win it!" (eBay Inc., 2007a) . In the corresponding television commercials, bidding in an eBay auction is compared to exciti ng sports events, such as football matches and dog races.

Finally, from the perspective of the participants in online retail auctions, it is important to highlight that arousal can affect their decision making. In the case of an ascending auction, this results in a smaller surplus for the bidders. However, being aware that arousal has an impact on their behavior may also help consumers to mitigate this effect. To this end, the deliberate application of emotion regulation strategies could be a promising approach. For instance, a bidder could apply cognitive reappraisal (Gross and John, 2003) by refraining from social comparisons and reassuring herself that winning the social competition is not so important. As a matter of fact, professional financial traders have already started using serious games with biofeedback in order to train their emotion regulation capabilities (Astor et al., 2014; Fenton-O'Creevy, 2012). Following this reasoning, it is reasonable to believe that providing users with real-time biofeedback may help consumers to become aware of their emotions, to better assess their own emotional processes, and to avoid impulsive and irreversible decisions with undesired outcomes.

3.5.3. Limitations and Future Research

There are several limitations that exist in the presented studies. First, although measuring bidders' HR provides an objective proxy for arousal, there are some shortcomings of this approach. A general problem is that usually some proportion of the measurements fails, which also happened in the first study. Another factor is that changes in arousal are not instantaneously reflected in changes in HR, as they are partly based on hormones (Berntson et al., 2007). Thus, in the moment a bidder clicks on the button to leave the auction, the actual level of arousal is not already fully manifested in HR. This may result in a systematic underestimation of the actual degree of auction fever in the first lab experiment (Chapter 2), i.e., the mediation of arousal on bids may actually be stronger than the analysis indicates. Ultimately, it even cannot be ruled out that arousal fully mediates the impact of time pressure on bids, as is the case in the second study in Chapter 3, where we use psychometric scales to measure arousal. Moreover, referencing HR values to the initial rest period does not fully eliminate interpersonal differences. In this study, we chose a conservative between-subjects design. However, this also means that HR values of different participants are compared when analyzing the mediating effect of arousal on bids, which may lead to some distortions. In general, by combining different arousal measures future research may contribute to the development of multi-factor arousal models that can provide a more detailed assessment of the emotional state. Such models could possibly overcome the limitations of a single-factor arousal model.

Second, the age of the participants and further personality characteristics may also be a correlate of physiological arousal; both due to anatomical as well as due to experience reasons. However, because both studies ware conducted with university students, the variance in age is very small, such that we cannot reliably control for this factor in the analysis. We cannot rule out, however, that there are further factors that can serve as moderators or mediators in the context of auction fever, e.g., personality traits such as neuroticism as well as emotion regulation capabilities, which were not considered in the studies. Therefore, disentangling these effects is an important area of future research in the field of retail auctions.

Third, the experimental design does not take into account the role of emotions in subsequent auctions, which may however lead to more intense interpersonal rivalries among bidders (Ku et al., 2005; Malhotra, 2010). For instance, everything else being equal, a bidder who has previously won an auction against a rival might experience more arousal during the auction and bid more aggressively, because she wants to re-experience this joy of winning. However, in order to study these effects in a systematic way, it would be necessary to control whether a bidder wins or loses. This is not possible with the presented design, in which the winner is determined endogenously.

Fourth, the experimental design differs between the first and the second study with respect to the length of the rest period between consecutive auctions. In the first study, we hold the rest period at constant length in all treatments. Although this design choice was made to achieve the greatest possible comparability between treatments, it also resulted in longer session lengths for the low time pressure auctions than for the high time pressure auctions. This may have led to an underestimation of the arousal levels in the low time pressure condition. Therefore, in the second study, we chose the length of the rest period for each treatment such that the overall session length is identical across treatments. The variation in rest period length in the second study, however, might in turn result in an underestimation of arousal values in the medium time pressure condition, because it increases the chance of participant fatigue. As the impact of time pressure on arousal is consistent in both studies, however, there is reason to believe that the influence of differences in rest period length is rather small.

In general, more research is needed to investigate the conscious and unconscious influence of arousal on consumer behavior. This includes both integral as well as incidental arousal. While integral arousal refers to the affective processes that are directly induced by the auction (e.g., auction dynamics, time pressure, rivalry), incidental arousal refers to affective processes that are induced by seemingly irrelevant environmental conditions. In this vein, also factors not directly related to an auction might trigger arousal, which ultimately has an impact on behavior. For instance, what is the influence of design elements embedded in the user interface (e.g., affective pictures, colors, design aesthetics) on the consumers' emotions and behavior? Can the consumers avoid the detrimental influence on their behavior by applying emotion regulation strategies? To what extent can external emotional influences fuel auction fever? Strictly speaking, external emotional influences on bids do not fall under the auction fever definition adopted in this paper. Yet, their direct and indirect influence on bids is an important area for future research.

Moreover, further research is needed to broaden the understanding of the drivers and the nature of integral arousal in both the presence and the absence of a social competition. In particular, while the results reveal that neither the desire to win nor the fear of losing serve as mediators for the influence of time pressure and social competition on bids, these factors should not be considered irrelevant for the nature of arousal in a social competition. In particular, the results show that the desire to win is an important driver of arousal and higher bids when bidders compete with human opponents. Further investigating these factors could therefore enhance the understanding of the nature of arousal in the presence or the absence of a social competition. It is even conceivable that computer opponents can become part of the social competition of auctions, for instance, by changing their graphical representation and other elements of the user interface.

3.6. Conclusion

In this chapter, we investigated the role of competitive arousal perceived in the social competition and its impact on bidding behavior in electronic auctions. To this end, we conducted a second laboratory experiment in which we used psychometric scales to measure and evaluate the bidders' perceived competitive arousal. In the experiment, bidders participated in ascending clock auctions with either no or medium time pressure, and either social competition or increased social competition. These changes in the treatment structure, which are implemented as a manipulations, confirmed the results of the previous study. Based on the results, we can again empirically (i.e., using psychometric measurements) establish a positive relationship between time pressure, social competition, bidders' arousal, and bidding behavior.

Taken as a whole, the studies in Chapter 2 and Chapter 3 highlight the importance of bidders' arousal—and emotions in general—in electronic auctions, such as retail auctions. On the one hand, marketers may utilize this knowledge to provide customers with an exciting shopping experience. This will not only serve as a means of differentiation to competing online marketplaces, but, in the case of ascending auctions, can also be monetized directly through increased revenues. In particular, the physiological and psychometric data show that auction fever really exists—but only when bidders compete with human opponents. Thus, social competition is the actual driver underlying the auction fever phenomenon. Auction participants, on the other hand, should be well aware of the influence of their emotions on their behavior.

Part III.

Supporting

Chapter 4.

Predicting Bidding Behavior Using Physiological Data

In this chapter, we investigate the problem of selecting useful physiological features (derived from physiological data) in a given context. Here, we use the context of an electronic auction setting—as it was introduced in Chapter 2—and the prediction of decision behavior, i.e., bidding behavior. Although, studies have show that physiological features can provide valuable insights into a decision-maker's affective processes, literature does not provide a general answer to how varying physiological parameters influences the quality of physiological features. As the quality of the physiological features highly accounts for the quality of the analyses, predictions, and support systems in which they are used, we seek to investigate an approach for systematically testing and validating the variation of physiological parameters in a given context. Thus this chapter focuses on Research Question 3, which states:

> **Research Question 3:** *How can evolutionary algorithms be used to select physiological features for predicting bidding behavior in electronic auctions?*

4.1. Introduction

The quality of economic decision-making, such as decisions in auctions, is not only dependent on the decision-maker's knowledge of the domain and experience. An increasing number of studies have revealed the correlation of a decision-maker's affective processes and the quality of decisions, where quality can be measured using various metrics such as accuracy, number of errors, or divergence from theoretically optimal behavior (e.g., Antoine Bechara and Antonio R. Damasio (2005); Fenton-O'Creevy et al. (2011); Ku et al. (2005); Lo and Repin (2002); Sanfey et al. (2003)).

However, due to the unconscious nature of one's own affective processes, it is especially difficult to be fully aware of one's own current emotional state and to utilize this valuable information (Vaitl, 1996). Driven by the autonomous nervous system (ANS), physiological responses to environmental factors are outside of one's conscious control and, therefore, they provide an unaltered insight into a decision-maker's affective processes. Using training and decision support systems for actively increasing the awareness of one's current state has been shown to improve and de-bias decision-making (e.g., Astor et al. (2014); Cochran (2011); Jercic et al. (2012)). Although unlocking access to a decision-maker's emotional state and the information hidden within could also be of important interest at a team or corporate level—e.g., a financial firm putting together a trading team (i.e., trading floor (Fenton-O'Creevy et al., 2012))—the implementation of this in a real-world information system (IS) and its integration in day-to-day use is still a long way off.

Even though the necessary tools (i.e., measurement devices and data analytic capabilities) for implementing such an IS have become ubiquitous during the past years, even for consumers (Al Osman et al., 2014), one particular problem remains: The immense variety of different measurements and their appropriateness to a given context. Derived from medical practice and research, every measurement of a human body's physiological activity (such as electrocardiography (ECG), electrodermal activity (EDA), and electroencephalography (EEG)) can be assessed using several different approaches. In ECG data, for example, the measurements range from simple calculation of beats per minutes (BPM) to computational complex frequency and special geometrical analysis. In addition, since those measurements are mathematical transformations of electrical signals, they also allow for a multitude of parameterizations, e.g., (i) the time window used for calculation, (ii) the values used for normalization, or (iii) the offset to an event used to detect changes in the measurement, resulting in a large amount of possible physiological features. Especially in a non clinical environment, such as an auction, where participants are not continuously observed for days or weeks but hours or even less, it is very challenging to derive meaning from existing standard measures (Schaaff and Adam, 2013; Salahuddin et al., 2007).

In addition to the immense variety of different measurements and features, analyzing physiological data is also challenging due to the fact that physiological data is usually very noisy (i.e., measurement limitations and disturbances) and multiple measurements are likely to be correlated (e.g., heart rate and respiration). This increases computational efforts and requires more fuzzy approaches that are able to perform well under such restrictions.

Using an Evolutionary Algorithm (EA), this chapter proposes a new approach to address the above-described problem. EAs have been proven to perform exceptionally well in situations where (i) there are too many possible solutions, (ii) there is no single best solution, and (iii) the solutions are heavily constrained (Blum et al., 2012). Since there is no theory based answer indicating which subsets of physiological measurements and measurement parameterizations would provide outperforming predictive power, we combine an EA with two different prediction models: Multiple Linear Regression (MLR) and Artificial Neural Network (ANN). Both, MLR and ANNs, are commonly used prediction models in a broad range of research areas for analyzing linear and non linear relations, respectively (see Hu, Bao, Xiong, and Chiong (2015); Hu, Bao, Chiong, and Xiong (2015); Xiong, Bao, Hu, and Chiong (2015) and references therein).

4.2. Dataset

To test and demonstrate this approach, we make use of a unique dataset built in previously conducted in the study in Chapter 2, in which the phenomenon known as auction fever was investigated in the context of an ascending clock auction. This auction format is one of the most used in today's retail and professional environments. In an ascending clock auction, the standing price increases automatically by a fixed time interval and participants only have the option to exit the auction (without the option of reentering) when the current standing price exceeds their personal reservation price. Other interactions, either with the auction system or with other participants, are not available to the participants. The auction ends when the second last participant exits it, leaving the last participant in the auction as the winner at the current standing price. Therefore, measuring auction time and auction prices is equivalent in this auction setting.

In this auction, the participants compete for a virtual good in every auction. The good's value (i.e., resale value) is described by a commonly known discrete and uniform distribution with a predefined range and an expected value at one-half of the range's length. The actual value of a good in each auction is randomly drawn from the distribution after a winner is announced and, therefore, is unknown ex ante. A profit is only gained by the winning participant, if the randomly drawn value is higher than the winning price. Otherwise, the participant generates a loss.

The study was conducted as a series of laboratory experiments at Karlsruhe Institute of Technology, Germany, in a controlled environment (e.g., consistent experimental protocol, controlled temperature and humidity levels, and limited participant interactions). Student participants were recruited to compete in a series of auctions at a time and the participants were incentivized using a monetary payoff related to their experiment performance. Three participants competed in an auction, whereby a random stranger (re-)matching approach was applied after each completed auction. Using this random stranger matching approach ensures that the groups of participants change between every auction and, therefore, participants cannot adapt to the strategy of a specific competitor. This reduces participant specific learning effects and increases inter auction independency. The participants had no further knowledge against whom of the other participants they were competing. Using a full factorial and between-subjects design, two treatment variables were used (time pressure and social competition) to vary the degree of auction fever to which the participants were exposed. The auction environment was implemented using zTree (Fischbacher, 2007) and the participants competed in 15 adjacent auctions. During these auctions, behavioral data (i.e., how long participants stay in the auction) as well as physiological data of the participants were simultaneously recorded. This unique combination of synchronized behavioral and physiological data comprises the dataset we use in this study (for further information on the dataset see Chapter 2).

In addition to the behavioral and physiological data, the dataset comprises demographic data on the participants, such as gender and risk aversion, as well as detailed information on the conducted auction. In the following, the behavioral and physiological data is described in more detail.

4.2.1. Behavioral Data

The behavioral data is based on the interactions of participants during the auctions. Figure 4.1 outlines the auction timeline including its main events.

Each auction starts with a rest period of 1 minute (in addition to an initial cool down period of 5 minutes preceding the first auction), which is used to establish the baseline of a participant's current physiological state. This baseline is later used to normalize physiological features, in order to reduce between subject variability and, therefore, increase generalizability of results. The subsequent auction has five main events: (i) the auction start, (ii) the start of the resale value range, (iii) the expected value, (iv) the auction exit, and (v) the auction end. Given the design of an ascending clock auction, only the first and last events (the auction start and auction end) are recorded for every participant and every auction. The remaining events do not occur for every participant in every auction, since they depend on the time of a participant's auction exit. If a participant chooses to exit the auction before the resale value range or the expected value is reached, then these events cannot be recorded. Similarly, if a participant wins an auction, no auction exit is recorded, since the participant wins the auction by being the last participant in it. The auction start event is used as a reference point for all later events of an auction, which are measured in milliseconds relatively to their current auction start (i.e., $t_s = 0 < t_r < t_v < t_e$).

In the analysis, we focus on the prediction of participants' auction exit t_x, which provides us with a dataset of 677 observations (only data entries, which include an auction exit event) from 60 participants of one treatment ($M = 11.28$ [$SD = 3.05$] observations per participant). If recorded, t_x occurs between the auction start and auction end ($t_s < t_x < t_e$).

4.2.2. Physiological Data

The physiological data consists of electrical activity measurements of the heart by means of a 3-lead electrocardiogram. The ECG signal was continuously recorded for each participant with a sampling frequency of 1 kHz. Before the data was used in this study, it was preprocessed to assure signal quality as well as proper heartbeat and inter-beat interval (IBI) detection. The IBI describes the time (in milliseconds) between two adjacent peaks in a heartbeat signal and it is the basis for most heart rate-based physiological features.

Heart rate, among other physiological features, provides a direct and quick insight into a person's current physiological as well as emotional state (Günther et al., 2010). By reflecting the activities of the ANS, physiological features reveal information that usu-

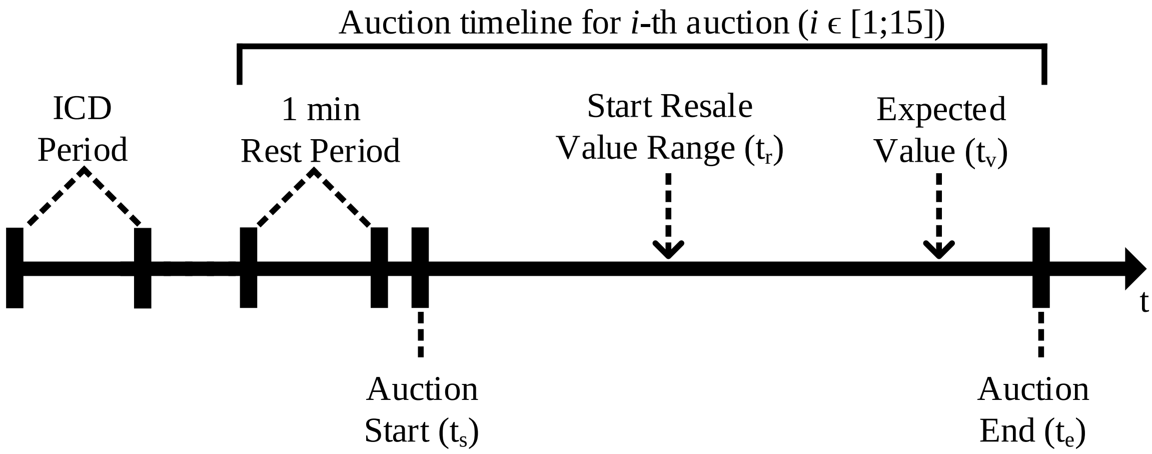


Figure 4.1.: An auction timeline showing the Initial Cool Down (ICD) Period, Rest Period (RP) and 4 auction events: t_s=Auction Start, t_r= Start Resale Value Range, t_v=Expected Value, and t_e=Auction End.

ally cannot be influenced by conscious control and is outside of conscious awareness (Andreassi, 2000). The ANS is responsible for balancing the so called "fight or flight" reflex on the one hand (sympathetic nervous system), and digestion and recreation on the other hand (parasympathetic nervous system). In recent years, this circumstance has successfully inspired the use of physiological features in other, non-clinical research areas, such as IS research, i.e., NeuroIS (Andreassi, 2000; Dimoka et al., 2012).
Heart rate in particular has been shown to accurately reflect the arousal dimension of a person's current emotional state (Andreassi, 2007; Ortiz de Guinea et al., 2013; Thayer et al., 2009). It increases in stressful situations and can influence (economic) decision-making (Adam et al., 2015).
After identifying commonly used heart rate-based physiological features and normalization methods from the literature (Malik et al., 1996), we implemented those physiological features using the Matlab HRV tools (Clifford et al., 2006). For each participant, 37 physiological features have been derived from their IBI data. Table 4.1 shows an overview of the physiological features and additional normalizations implemented for this study.

In order to calculate the physiological features listed in Table 4.1, an observation window has to be defined. This observation window selects the range of IBI data to be used for the calculation of a physiological feature and it is defined by three parameters: (i) window size, (ii) offset, and (iii) selection type. The window size defines the timespan (i.e., the range), which is used as input for calculating the physiological feature. The offset defines the distance of the observation window's end to the event to which it refers (i.e., the auction start event). For example, for a given window size, an offset of zero selects an observation window, which ends exactly at the time of the event, whereas an offset of minus 10 milliseconds selects an observation window of the same window size, which ends 10 milliseconds before the time of the event (analogous using positive offsets). Lastly, the selection type of an observation window defines on what basis the selections of window size and offset are performed. In the case of heartbeats, the selection types are either millisecond-basis (such as the previous example) or heartbeat-basis (i.e., number of beats). Table 4.2 provides an overview of the observation window parameters.

By combining all physiological features and observation window parameters (e.g., hrMean, window size $15,000\ ms$, and window offset $-500\ ms$), there are a total of $N = 5772$ possible predictors, i.e., candidate features (CFs), for the prediction models.

4.3. Methods

The approach is built on two elements: First, an EA to select a subset of the available CFs and, second, a prediction model to evaluate the selected subset. The implementation is realized in Matlab (version R2015a), and, where possible, built-in functions are used to avoid reimplementation. Figure 4.2 illustrates the entire approach as a flowchart.

4.3.1. Performance Metrics

We use two performance metrics (i.e., fitness values) to evaluate the results: Minimization of the subset size S (i.e., number of selected CFs) and maximization of the prediction model's predictive power (i.e., R^2 error metric).
As the problem at hand is of high dimensionality (i.e., far more CFs than observations), it is statistically possible to select a big enough subset of CFs ($\geq$ number of observations), which almost perfectly explains the given dataset (i.e., overfitting [29, 30]). Furthermore, we seek to provide practical solutions that are applicable to real-world ISs. Therefore, a smaller subset size S is always preferable, as it directly relates to less computational effort. However, it is not possible to determine a priori the minimal (nor optimal) subset size S that provides sufficient predictive power.
To measure the predictive power of the prediction model, we chose the commonly used R^2 error metric. This metric determines the quality of a prediction model in relation

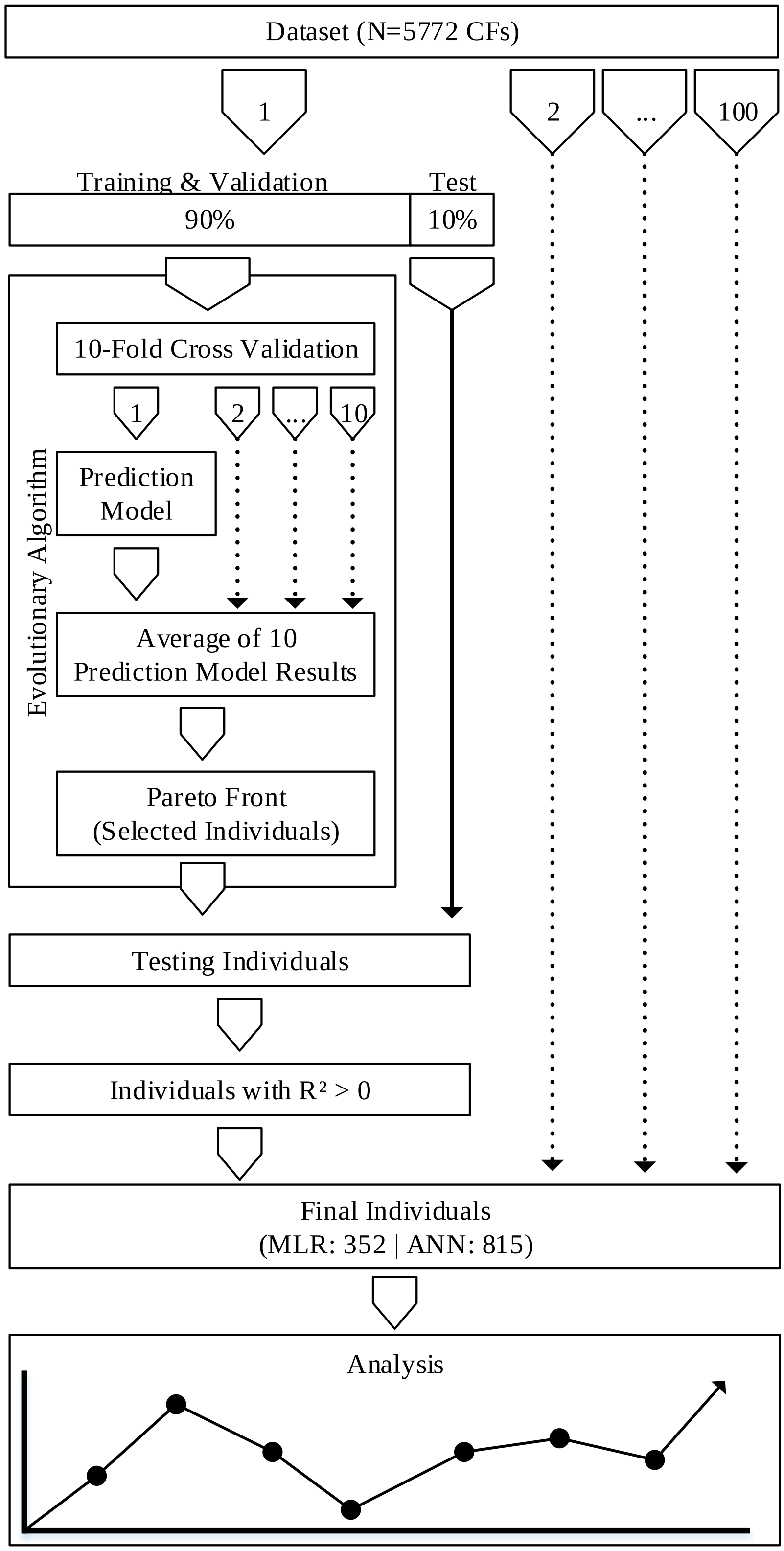


Figure 4.2.: A flowchart of the proposed approach.

Table 4.1.: Overview of physiological features.

Feature	Additional Normalization	Description
hrMean	RP, ICD, Log	Mean heart rate (HR)
ibiMean	RP, ICD, Log	Mean inter-beat interval (IBI)
ibiMean	RP, ICD, Log	Mean heart rate (HR) ($X \in$ [Low Frequency (LF), High Frequency (HF), Ratio of LF/HF])
hrvX	RP	Heart rate variability ($X \in$ [Low Frequency (LF), High Frequency (HF), Ratio of LF/HF])
pNNX	RP	Adjacent IBIs smaller than $X \in [12, 20, 50]$
rmssd	RP	Root mean squared standard deviation of adjacent IBIs
sdX	RP	Standard deviations of Poincaré Plot $X \in [1, 2]$
sd1sd2	RP	Ratio of sd1/sd2
sdnn	RP	Standard deviation of adjacent IBIs
renyi entropyX	-	Renyi Entropy based on $X \in$ [Ruler, Histogram]
fractal dimension	-	Fractal dimension based on IBIs

Normalization:
RP=Rest Period; ICD=Initial Cool Down Period; Log=Log-Transformed

Table 4.2.: Table of Observation window parameters.

Window Sizes	Window Offsets	Selection Types
10,000; 15,000; 20,000	[-10,000; 0] in 500ms increments	Milliseconds (ms)
10; 15; 20	[-10; 0] in 1 beat increments	Heartbeats (b)

to the naïve assumption of always predicting the observation mean. In addition, the metric is independent of the actual type of prediction models as it is not model specific. The calculation is as follows:

$$R^2 = max(0; 1 - \frac{\sum(a-f(a))^2}{\sum(a-\overline{a})^2})$$

where a represents an observation, $f(a)$ is the prediction of a for a given model, and $\overline{a}$ the mean of a of the given dataset. Values close to zero indicate poor predictive power, while increasing values indicate increasing predictive power.

Since the relation and weighting of the two performance metrics (number of selected CFs and the model's predictive power) are also not known a priori, the metrics cannot be combined into a single metric (e.g., by a ratio or a scalar product). This makes the proposed research question a multi-objective optimization problem.

4.3.2. Evolutionary Algorithm (EA)

The EA is applied as a wrapper method (Hu et al., 2015; Kohavi and Kohavi, 1997) for selecting subsets of CFs. As outlined above, the proposed problem is a multi-objective optimization problem, and therefore we use the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002). Like all EAs, the NSGA-II is a population-based metaheuristic for finding solutions in a complex search space. By starting with randomly initiated solutions and evolving them over time (favoring solutions based on their fitness values), EAs are able to converge to a globally optimal solution. However, the NSGA-II is specially designed for multi-objective optimization, aiming to minimize multiple performance metrics. To account for the contradiction with the performance metric R^2 (needs to be maximized), we multiply R^2 by minus one and use negative R^2 instead. The solutions computed do not consist of a single best individual (i.e., subset of CFs) but multiple feasible individuals, i.e., the Pareto front (Weise et al., 2009, 2012). Individuals qualify to be included in the Pareto front are Pareto dominant, which means that their fitness based on both performance metrics are at least as good as the corresponding performance metrics of all other individuals, and there is at least one performance metric that strictly outperforms the corresponding performance metric of every other individual. In addition, the NSGA-II favors solutions that are less crowded within the search space, in order to increase sparsely used areas (i.e., favor diversity). Recalling the initially proposed problem, the NSGA-II is therefore an appropriate choice for this approach. For further reading on the NSGA-II and EAs in general, see Blum et al. (2012); Deb et al. (2002).

The EA is implemented such that each individual (x_i) represents one subset of CFs (i.e., genotype). The subsets are modeled using a binary string approach, which means that every subset consists of N binary values—each representing one CF. If a CF is selected to be included in the following computation, it is assigned the value one, whereas zero is assigned to CFs that are excluded. Given the binary string approach, reproduction is performed using a uniform crossover operator in combination with a random flip-bit mutation operator.

Since one requirement of this approach is the applicability to real-world ISs, the limit of CFs for valid solutions is arbitrarily set to a maximum of $S_{max} = 50$ CFs per individual x_i. The individuals are all initialized with 25 randomly selected CFs ($S_{init} = 25$). Table 4.3 shows an overview of all settings used to parameterize the above-described EA.

Table 4.3.: Settings used for the NSGA-II.

Parameter	**Value**	**Parameter**	**Value**
Population Size	250	Selection Type	Tournament
Populations	5	Mutation Type	Random Flip (25%)
Crossover Type	Uniform (80%)	Migration Direction	Forward (1%)
Elitism	5%	Migration Interval	10

4.3.3. Prediction Models

CFs selected by the EA are used as inputs (i.e., predictors or independent variables) for the outcome variable, the auction exit (i.e., the dependent variable). We apply two different prediction models to determine the predictive power of a particular subset of CFs: MLR and ANN.

The MLR model analyzes linear relations between the model's independent variables (i.e., CFs) and the outcome variable. Although physiological measurements often show a non-linear characteristic, using a linear model is still feasible considering the CFs. By additionally using, for example, log transformed and normalized physiological measures, we reduce the potential impact of non-linear characteristics to exhaust the strengths of a MLR model. The MLR model is formulated as follows:

$$y = \alpha + \sum \beta_i CF_i + \epsilon$$

where y is the dependent variable, α the intercept, S is the size of a given subset, β_i the i-th model coefficient, CF_i the i-th CF of the given subset, and ϵ the model residuals. To estimate the coefficients, the standard method of least squares is used.

The nature-inspired ANN is a statistical learning method, which uses a weighted graph of inter-connected neurons to find relations (linear and non-linear) between its input neurons and a given output. Although ANNs are often referred to as a "black box" approach, their outstanding predictive power in the realm of time series forecasting and classification fostered their use in a wide area of research and real-world ISs, such as in finance, health, ecology, and biology (Chiong et al., 2010). For the ANN model, we implement a basic feedforward Multilayer Perceptron, using two hidden layers and a default Levenberg-Marquardt backpropagation learning algorithm (Hagan and Menhaj, 1994). The number of neurons per layer is adjusted depending on the current subset size S. That is, the input layer has S neurons, the first hidden layer has $\lceil \frac{2}{3} * S \rceil$ neurons, the second hidden layer $\lceil \frac{1}{3} * S \rceil$, and the output layer consists of a single neuron.

4.3.4. Robustness

To increase the robustness of the analysis, the entire dataset is randomly split by participants into three distinct segments prior to the analysis (Wang et al., 2011). We use 90% of the dataset for training and validation, and the remaining 10% for testing. The training and validation data is then further used to generate a 10-fold cross validation dataset. This cross validation is applied to each iteration and individual, so that the R^2 of an individual per iteration is the mean of the 10-fold cross validation outcomes. After the EA computation is completed, the test dataset is applied to the selected individuals. Only those individuals are considered in the results, which also yield a $R^2 \neq 0$ using the test dataset.

Moreover, due to the stochastic nature of the EA and the high correlation of some CFs (e.g., mean heart rate of a given window size and the offset of one beat with the offset of two beats), we do not expect the result to be a single dominant individual. Given the initial random seed, which is relevant for the "random" steps of any EA, two individuals could create an equal fitness value but consist of different (but mostly similar) CFs. To counter this, we run the approach 100 times over both prediction models, each with different initial random seeds. We then statistically test all individuals for the final solution.

4.4. Results and Discussion

The approach results in 352 and 815 individuals for MLR and ANN, respectively. Each individual x_i represents one distinct solution. The large number of distinct individuals is a result of the high correlation among some CFs, as described above. All presented statistical results are tested against a 5% significant level.

4.4.1. Descriptive Results

First, we inspect the process of the EA's improvements over time. Figure 4.3 shows the results based on the two performance metrics, mean number of CFs (upper graph) and mean predictive power (lower graph), on a normalized time scale. Inspecting the mean number of CFs, we can see that the two prediction models have similar progress over time. For the mean predictive power metric, however, the ANN model outperforms the MLR model. Recall that an increasing value of R^2 (i.e., decrease in negative R^2) indicates improvement.

Next, we inspect an overview of the predictive power of all solutions grouped by the number of CFs that each solution contains, i.e., the mean over all Pareto fronts, including standard deviations. This is shown in the upper graphs of Figure 4.4. The lower graphs in Figure 4.4 show the number of solutions with different numbers of CFs. These two types of graphs are shown in Figure 4.4 for the MLR (on the left) as well as the ANN (on the right) models. As expected, the most powerful predictive capability is achieved by solutions containing the most CFs ($CFs = 20,\ R^2 = 0.1810$). However, there is only one such solution. Recall that all individuals were initialized with 25 CFs and the arbitrary maximum number of CFs was 50-both are greater than the number of CFs in any solution.

Figure 4.5 provides a summary of the physiological features that appear in the final solutions. The bars in Figure 4.5 are composed of stacked bars showing the selection

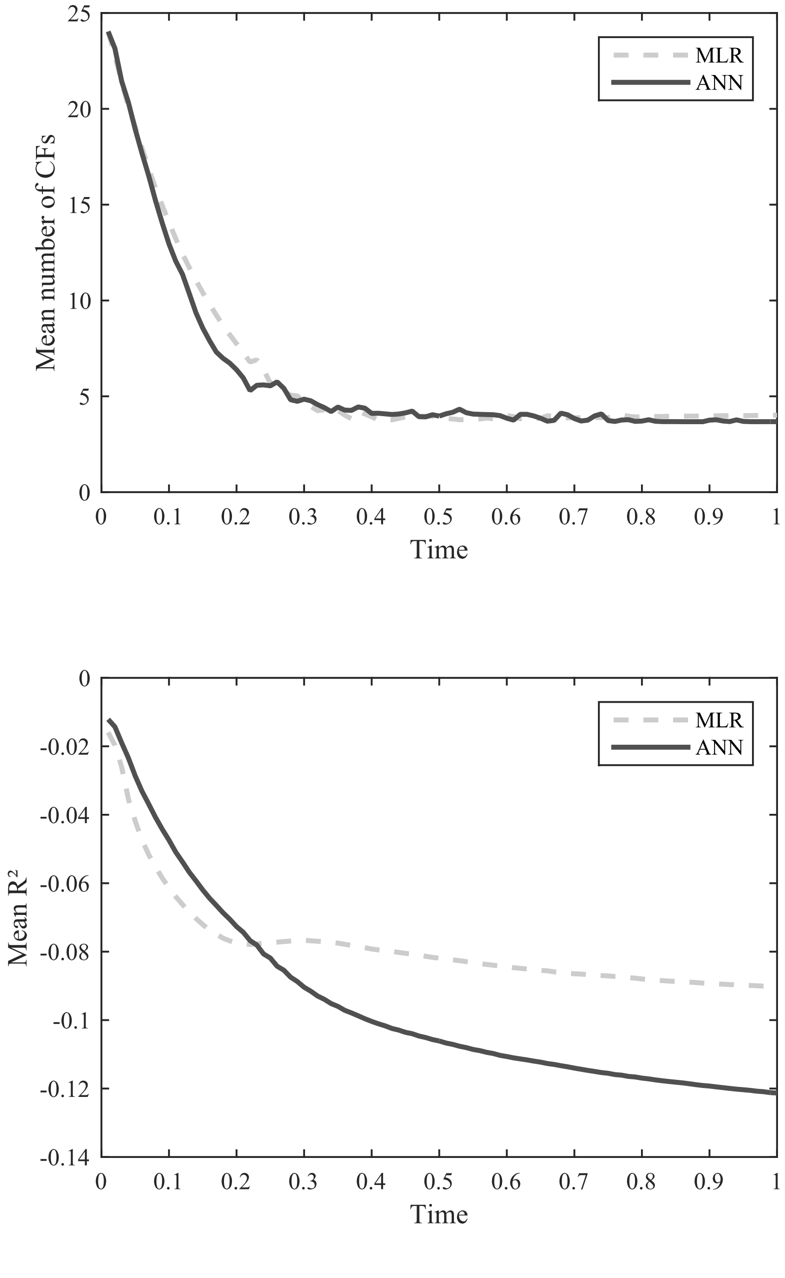


Figure 4.3.: Improvements of EA over time.

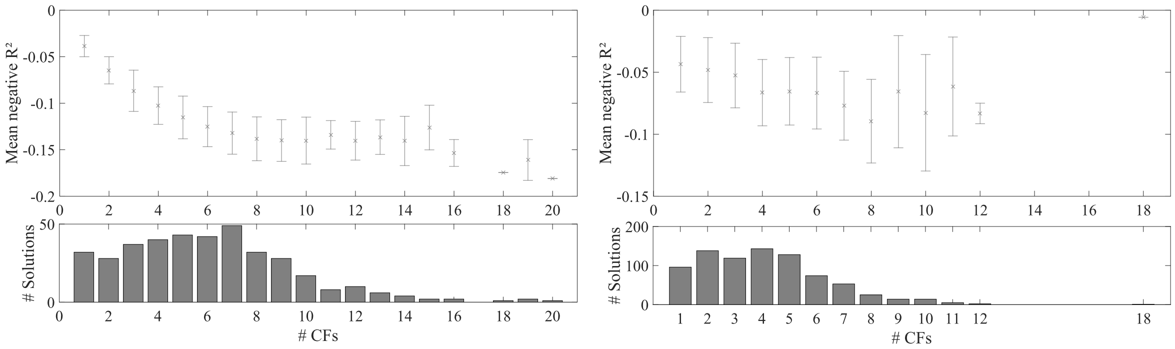


Figure 4.4.: Mean EA results for the MLR (left) and ANN (right) models. Upper graph: Mean negative R^2 with standard deviation (y) by number of CFs (x). Lower graph: Number of solutions (y) containing number of CFs (x).

type ms (lower bar) and beats (upper bar). The figure shows that the selection type ms is more often selected than beats. Based on a two tailed Mann Whitney U test, these results are found to be significant for the MLR model (*ms* [$M = 42.62$], *beats* [$M = 20.16$], $U = 442.0$, $p < .01$) as well as the ANN model (*ms* [$M = 63.54$], *beats* [$M = 25.83$], $U = 406.0$, $p < .01$). In addition, Figure 4.5 shows that the most often selected physiological features are heart rate and IBI-based CFs as well as rmssd. Frequency and geometric based CFs are rarely selected.

Figure 4.6 provides an overview of the distribution of window sizes and offsets. It is shown that positive offsets ($oP*$) are more often selected than negative offsets ($oN*$) (cf. Table 4.4). This is to be expected because a positive offset means that the selected data is closer to the auction exit event that we are predicting. However, the analysis also reveals that this naïve assumption does not hold in the case of selection type beats and ANN as well as selection type ms and MLR (i.e., $p > .05$).
Analyzing the selections of window sizes as shown in Figure 4.6, the results indicate no significant difference for any window size (i.e., comparison of all window size tuples result in $p > .10$).

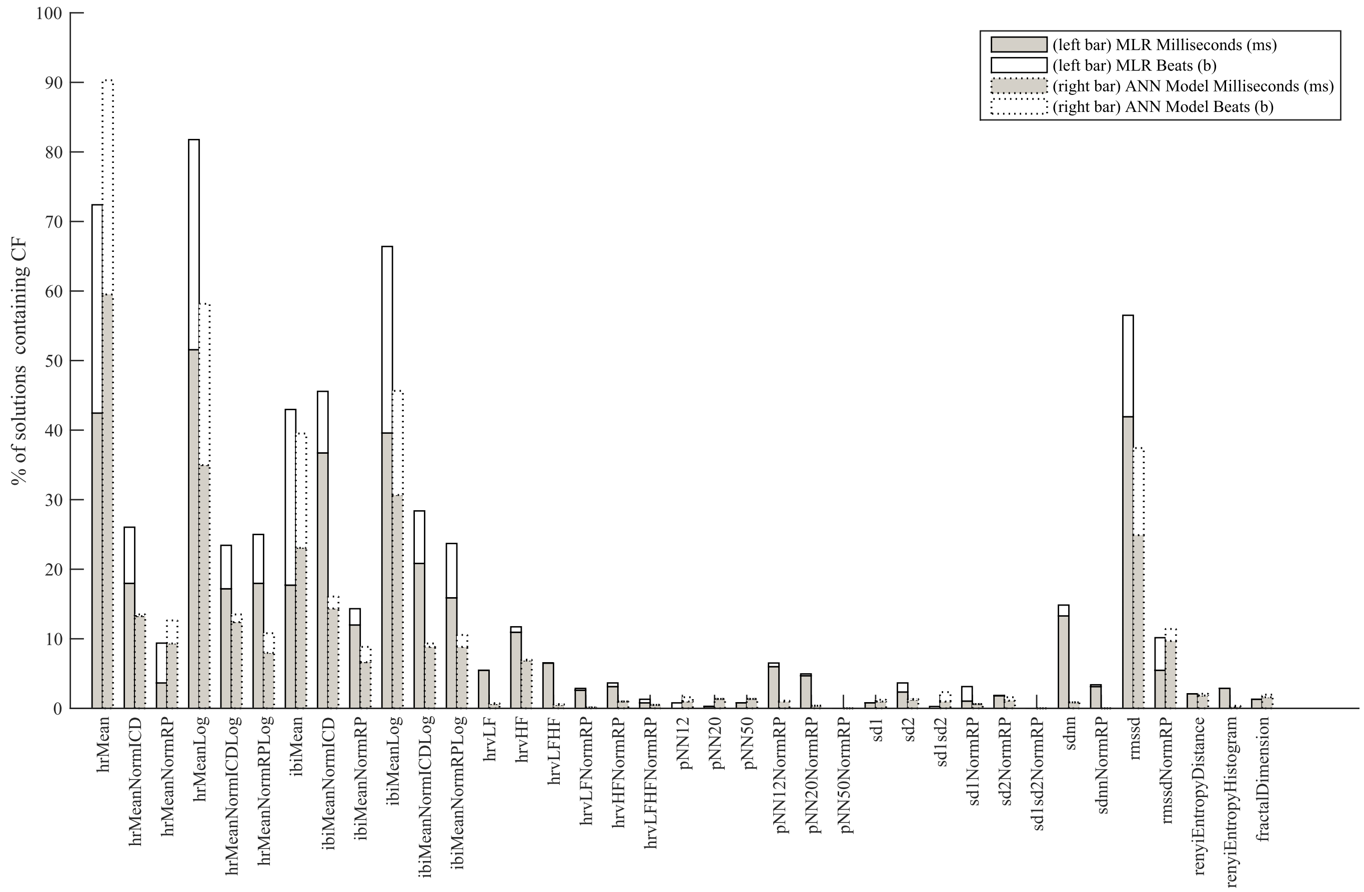


Figure 4.5.: Occurrences of physiological features in EA solutions. Bottom bar: Selection type ms. Top bar: Selection type: beat. Left bar: MLR. Right bar: ANN.

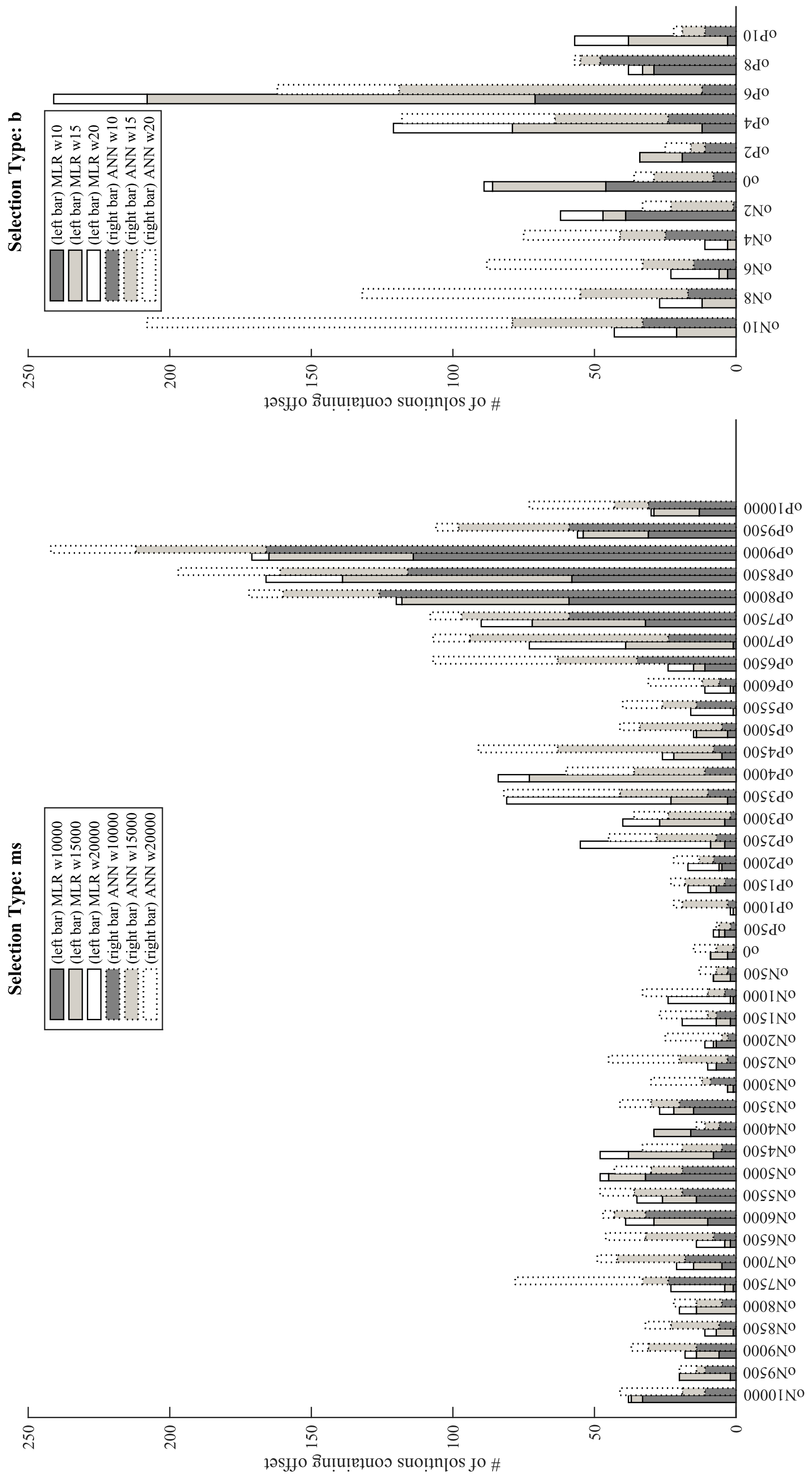


Figure 4.6.: Occurrences of window sizes and offsets in EA solutions. Left figure: Selection type ms. Right figure: Selection type beat. Left columns: MLR. Right columns: ANN.

Table 4.4.: Table of Two tailed Mann Whitney U test results on selection of offsets.

		Mean			
Selection Type	**Model**	***oN****	***oP****	**U**	***p***
Ms	MLR	7.77	18.37	2155.5	.062
	ANN	12.07	26.87	2395.0	.002
Beats	MLR	11.07	32.73	162.5	.039
	ANN	35.75	25.60	79.0	.171

4.4.2. Limitations

The results show that there are indications of preferences on specific CFs over others in order to gain predictive power. Of course, it is not possible to draw general conclusions based on the presented results, as the results are only valid for the given dataset and the decision-maker context it represents. However, the goal of this paper is to present an approach capable of selecting proper CFs for a given context. The CFs selected in the final solutions have to be taken with caution. We did not optimize the prediction models for the presented context but mostly relied on provided standard settings of the model implementations. It is possible that by adjusting the prediction models or introducing different models, the final solutions could further improve.

In addition, analyzing physiological data is always difficult because changes in a participant's physiology might not always be due to the observed event but external factors. This fact was taken into consideration by including the data of 60 participants recorded in a controlled laboratory environment to reduce external distraction in the best possible way. Also, recent studies indicate that the source of a change in physiology (e.g., arousal) does not matter to its later impact on behavior (Ku et al., 2008; Storey and Workman, 2014).

4.4.3. Implications and Future Work

The approach has been demonstrated to be able to select physiological features that can predict auction behavior. With this, utilizing physiological information is a step closer to become more feasible in real-world ISs. In combination with today's ubiquity of physiological sensors and existing theoretical models (e.g., Adam, Krämer, Jähnig, Seifert, and Weinhardt (2011); Adam, Gamer, Krämer, and Weinhardt (2011)), the approach can be used to enhance (existing) ISs. Such enhancements (e.g., Neuro-Adaptive ISs and biofeedback) can support decision-making and potentially mitigate biases in a given decision-making context (Lux et al., 2015). Although the additional information provided by the physiological information might appear limited, in a decision-making context, such as electronic auctions, the smallest advantage over one's competitors can make the difference between being first and being out of business. For example, in high stake situations, advising a trader to avoid taking unnecessary risks can prevent excessive monetary losses.

Certainly, future work is necessary to further this research and improve the results presented in this study. Using the approach in combination with additional CFs (e.g., "arousal meter" (Hoover and Muth, 2004)), physiological measurements (e.g., EDA) and auction events (e.g., outcome of preceding auctions) will provide promising research opportunities and more precise prediction for a given decision-making context. Especially for electronic auctions, the approach can be used to compare the role of physiological measurements in different auction settings (Astor et al., 2013; Adam et al., 2012), in order to determine bidding behavior and modify the underlying user interface or auction design accordingly. Even new auction designs that incorporate physiological information into the auction process itself are possible. This could increase excitement, affect bidding behavior, and provide additional hedonic value to participants.

The CFs found to have more predictive power than others can also be of interest to researchers of other disciplines. Disciplines such as medicine and psychology can build on these results and investigate further relations of the underlying processes driving a decision-maker's behavior.

4.5. Conclusion

This chapter has presented a working approach for selecting physiological features (i.e., physiological measurements and their parameterization) in the context of predicting bidding behavior in an electronic auction setting. Using the presented approach can potentially improve analyses, prediction, and real-world ISs (such as decision support systems, Neuro-Adaptive ISs, and education support systems), as they can better profit from the hidden information that physiological data provides. Especially in the electronic auction context, which generally is a fast pace environment, every small piece of information can have tremendous advantages and making the most out of one's own physiological information can lead to a significant impact.

Chapter 5.

Using Physiological Feedback in IS Research

Chapter 5 reviews and analyzes Live-Biofeedback (LBF) in the context of IS research and its potential for building LBF support systems. LBF systems use a person's physiological data to create instant (i.e., live) feedback in the person's current context. The physiological data is measured using various and sometimes simultaneously used sensors, such as heart rate, skin conduction, and respiration. The feedback output can consist of a single or multitude of outputs, such as visual, auditory, and tactile. This feedback is then used by the receiving person to induce a desired behavioral change. Especially, in the context of decision-making in electronic auctions, LBF has be shown to promisingly reduce behavioral biases. In order to gain a better understanding of the systematical effects and potential of LBF as support system, this chapter thus focuses on Research Question 4, which states:

> **Research Question 4:** *How can Live-Biofeedback be used in NeuroIS research to support decision-making in electronic auctions?*

5.1. Introduction

Live Biofeedback (LBF) processes real-time data of body signals (i.e., neurophysiological data) in order to provide users with information about their current emotional state. As the current emotional state can have significant influence on one's immediate behavior, being aware of this state provides an additional edge, as it allows to consciously counter undesired behavior and better learn from previous experience. LBF is used for therapeutic medicine, where LBF has its origin in the late 1960s (Green, Green, and Walters, 1969; Green, Walters, Green, and Murphy, 1969), as well as for healthy individuals, such as pro-athletes, to analyze and increase performance. Lately, due to increased ubiquity of sensors (e.g., in smartphones and consumer fitness devices), advances in computer science and computational power, and decrease in cost-per-use, LBF became also accessible to the general public (i.e., consumers). However, although nowadays systems commonly fulfill the requirements for implementing LBF, most research that combines information systems (IS) and neurophysiological data focuses on collecting data to complement post-hoc analyses. Consequently, little research is done to understand how to best design and apply ISs that incorporate LBF as well as how users react and interact with them.

We see two main reasons for the little research done on LBF in IS research as of now—both emphasizing our aim to assist and encourage IS researchers in conducting LBF studies. First, many IS scholars still have little to none experience in using neurophysiological data, or the knowledge of standards and common practices because using neurophysiological data in IS research is still a relatively young idea. Only in 2009, a subfield in IS research was formed, called NeuroIS, that focuses on this topic (Loos et al., 2010). Second, LBF requires collecting, processing, and analyzing neurophysiological data in real-time. These requirements pose additional challenges beyond the post-hoc analysis. However, overcoming these challenges offers numerous new research opportunities for IS scholars to further deepen the understanding of Human-Computer Interaction (HCI).

In this chapter, we provide insights into the field of LBF in IS research. We will focus on live (i.e., real-time) feedback of neurophysiological-based information in IS and devices that are applicable in a non-clinical real-world environment. To this end, the chapter makes three core contributions. First, we provide an integrative theoretical framework for LBF and how it can be integrated into IS research. Second, a systematic literature review of LBF in the IS research and related research areas. Third, an overview of potential application areas for LBF in IS research and related reseach areas, as well as in real-world applications.

5.2. Theoretical Foundations

5.2.1. Neuro-Adaptive IS and Live Biofeedback

To classify the varying degree to which neuroscience is applied in IS research, we refer to the paper of vom Brocke et al. (2013). The authors present a taxonomy of three hierarchical application strategies that distinguish and explain the major areas of applying NeuroIS. The strategies are: Strategy 1, use of neuroscience theories to inform the building and evaluation of IT artifacts. Strategy 2, use of neuroscience tools to evaluate IT artifacts. Strategy 3, use of neuroscience tools as built-in functions of IT artifacts. In the past, many publications have focused on topics relating to Strategy 1 and 2. Only recently, the increase in commercially available sensors (and their decrease in costs per use), the advance in computer science, and the insights gained in previous Strategy 1 and 2 related studies made it feasible to focus on Strategy 3, such as this study.

Next, we briefly introduce LBF in relation to its two parent research areas, namely NeuroIS and Neuro-Adaptive IS. NeuroIS, Neuro-Adaptive IS, and LBF comprise the concept of applying theories, methods, and tools from neuroscience and neurophysiology to IS research (and information and communication technology (ICT) in general). Therefore, the three research areas are situated in an environment where users interact with IS and their behavioral data (i.e., interaction with the IS, such as decisions, mistakes, and task performance) as well as their neurophysiological data (e.g., heart rate, skin conductance, brain activity) are correspondingly recorded and processed. In the following, we introduce the three research areas and their relation in further detail, as they are illustrated in Figure 5.1.

NeuroIS

NeuroIS, a subfield in IS research, uses neurophysiological theories, methods, tools, and measurements to better understand the design, development, and use of IS. A comprehensive definition is provided by Riedl et al. (2009). By applying neuroscience and neurophysiology to IS, NeuroIS is able to provide insights into visceral and previously hidden processes of the human body that influence user behavior and HCI. Especially, since many aspects of user behavior are instinctively and unconscious, users often are not aware of such aspects and, therefore, are not able to verbalize them. The NeuroIS approach complements this aspect (Tams et al., 2014), which affects traditional methods

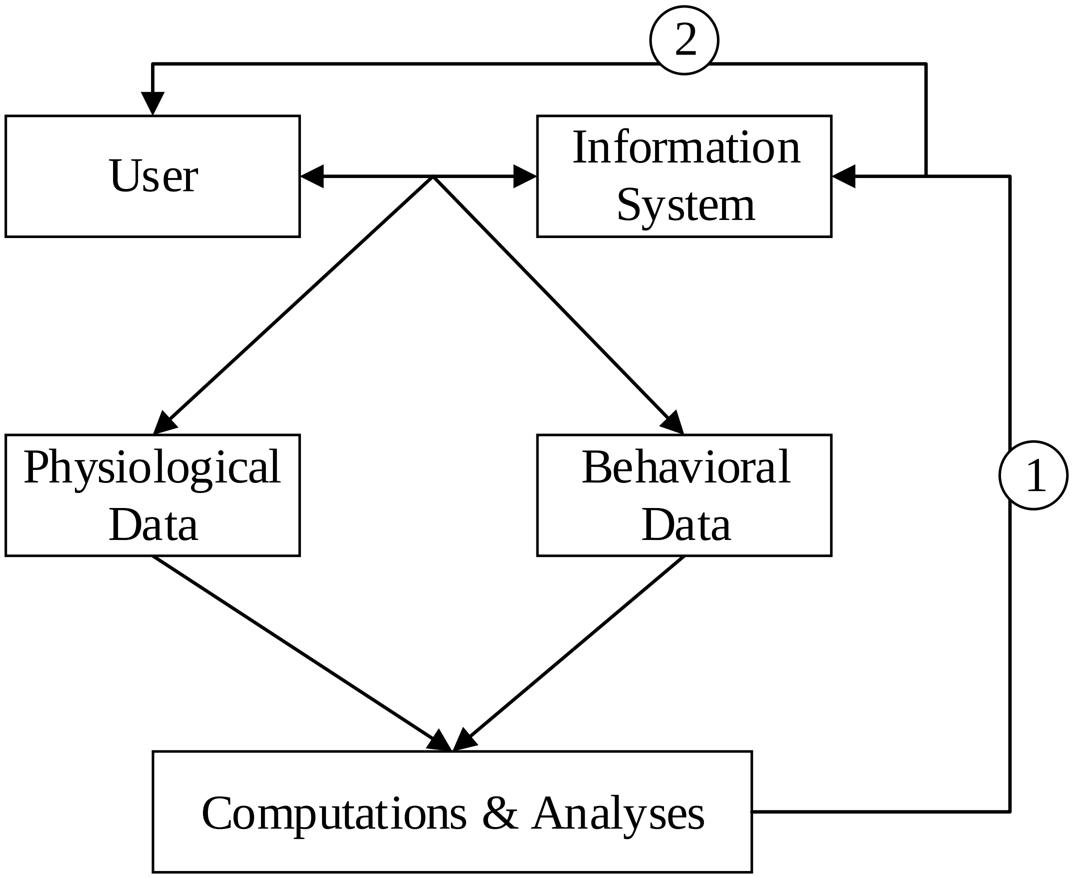


Figure 5.1.: NeuroIS: Applying cognitive neuroscience and neurophysiological theories and tools to inform IS research.
(1) Neuro-Adaptive IS: change properties of information system according to the user's current state.
(2) Live Biofeedback: Provide users with information about their physiology to induce changes in behavior.

for collecting survey data, such as questionnaires and interviews. To this end, neurophysiological data and its use in IS are seen as a complement to existing IS research methods—not a replacement. The types of data used in NeuroIS include neurological data (i.e., brain activity, such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), near infrared spectroscopy (NIRS)), as well as neurophysiological data, such as heart rate, skin conductance, and respiration, is considered by NeuroIS scholars and used to complement IS research.

For further reading on NeuroIS see, for example, Dimoka et al. (2012); Dimoka (2012); Dimoka et al. (2007); Riedl and Rueckel (2011); Riedl et al. (2009, 2014); vom Brocke and Liang (2014).

Neuro-Adaptive IS

The concept of Neuro-Adaptive IS was first introduced by the name of Affective Computing that is defined as "computing that relates to, arises from, or influences emotions" (Picard, 1995, p. 1). This means, the idea of computers being able to read and interpret a user's neurophysiological data and, as a consequence, react and respond to it. This definition is not limited to affect-aware interfaces but also extends to stationary and mobile (i.e., wearable) devices, continuous and situational scenarios, as well as single and multi-modal (i.e., multi-sensory) systems. Following Affective Computing, the term Proactive Computing (Tennenhouse, 2000) became increasingly prominent in the IS literature. Here, the idea of using neurophysiological data in IS extends to not only reacting to current user behavior but to also anticipating future behavior and predict appropriate actions, e.g., Kandemir and Kaski (2012). Lately, the term Neuro-Adaptive IS is used to describe IT artifacts (vom Brocke and Liang, 2014) and IS "that recognize the physiological state of the user and that adapt, based on that information, in real-time" (Riedl et al., 2014, p. 1).

According to the previously state definitions of application strategies, Neuro-Adaptive IS also classifies as Strategy 3, where neurophysiological data is used as a built-in function of IS. As such, it is a subcategory of NeuroIS.

As of now, "there is still considerable ground to be covered before affect detectors can be integrated into everyday interfaces and devices and can be more readily deployed into real-world contexts" (D'mello and Kory, 2015, p. 2). But Neuro-Adaptive ISs have successfully been demonstrated in research and there is an increasing number of (research) areas adapting the idea of Neuro-Adaptive IS, such as serious gaming (Astor et al., 2014), playful gaming (Garner and Grimshaw, 2013), and technostress (Riedl, 2013; Djajadiningrat et al., 2009).

Live Biofeedback (LBF) in IS

As a subcategory of Neuro-Adaptive IS, LBF also classifies as a Strategy 3 application strategy. However, in contrast to the previously described Neuro-Adaptive IS, the adaptation of the system is limited to real-time changes of the biofeedback indicator, such as its intensity or appearance. Other properties of the IS remain unaffected by the current state of a user. Figure 5.2 illustrates these two types of changes in an IS. Whereas this distinction between Neuro-Adaptive IS and LBF is useful in research, in practice, a combination of LBF and corresponding changes in the properties of IS is easily conceivable.

Figure 5.2.: Relation of NeuroIS and the subfields Neuro-Adaptive IS and LBF.

To provide a formal and exhaustive definition of LBF, we will refer to the definition of biofeedback as published by The Association for Applied Psychophysiology and Biofeedback (AAPB), the Biofeedback Certification International Alliance (BCIA), and International Society for Neurofeedback and Research (ISNR). The term biofeedback was also introduced by the AAPB in 1969 at their first annual meeting:

"Biofeedback is a process that enables an individual to learn how to change physiological activity for the purposes of improving health and performance. Precise instruments measure physiological activity such as brainwaves, heart function, breathing, muscle activity, and skin temperature. These instruments rapidly and accurately 'feed back' information to the user. The presentation of this information—often in conjunction with changes in thinking, emotions, and behavior—supports desired physiological changes. Over time, these changes can endure without continued use of an instrument." (AAPB, 2008)

Especially, the last statement of this definition (i.e., "over time, these changes can endure without continued use of an instrument.") separates LBF from the previously introduced NeuroIS and Neuro-Adaptive IS. This statement emphasizes that the focus of LBF is on the human behavior, rather than the properties (and therefore behavior) of an IS.

In comparison to other Neuro-Adaptive IS, LBF can include but does not require an artificial affective state model. Rather than using a user's neurophysiological data to artificially model and estimate a current affective state, LBF processes a user's neurophysiological data only for the purpose of creating feedback. The interpretation and choice of appropriate action is done by the user, which makes LBF much easier to implement and use in research as well as real-world applications. As existing (or legacy) ISs can rarely be enhanced to become Neuro-Adaptive ISs, LBF can easily be appended. Without interfering with the main functionality of an existing IS, LBF can co-exist (e.g., as an individual application or on a dedicated hardware) as it focuses on providing additional value to the user—not modifying the main IS itself. The added value of LBF is creating neurophysiological information from raw neurophysiological data. Further, LBF can be applied in a context where inferring an explicit action by the Neuro-Adaptive IS is not possible, because there are too many possible options or determining a best or preferred action is not possible (e.g., buy or sell indication for a stock in a financial market).

To sum up and in order to highlight the most important aspects of biofeedback for the IS-community, we define LBF as the real-time feedback of users' physiological activity through the system's interface.

5.2.2. Integrative Theoretical Framework on LBF

The effect of LBF has been the focus of medical and psychology researchers for many years (Schwartz and Schwartz, 2003), who, over time, have built the foundation for increasingly detailed theories and models on how and why LBF has an effect (e.g., Green and Green, 1999). However, as it is not our intention to contribute to the theoretical understanding of LBF, but to bring LBF to the attention of IS research, we further on rely on a necessarily oversimplified understanding of LBF . Based on a structured review of the literature, we propose an integrative theoretical framework (cf. Baumeister and Leary, 1997) that illustrates the relations between LBF and user behavior in an IS context. The framework is shown in Figure 5.3. It comprises two parts: Relations A, B, C that represent the established relations of the "User Environment," "Physiological State," and "Perceived Emotion" towards "User Behavior." In addition, the framework includes moderations 1, 2, and 3 that represent LBF moderations found in existing literature.

Established Relations

Relation A refers to the role of affective processes in determining user behavior (Winkielman and Berridge, 2004), such as as decision-making (Virlics, 2013). Research at the nexus of information systems and psychology has shown that user behavior is the result of complex interplay of cognitive and affective processes, providing evidence for a definite impact of affective processes on user behavior, which is measured, for example, by decision-quality (Adam et al., 2015), risk-taking (Lerner and Keltner, 2001; Lo and Repin, 2002), or trust (Riedl et al., 2011). Importantly, the influence of affective processes can occur beyond the user's conscious awareness (i.e., "affective information processing" by Walla and Panksepp, 2013) and is often perceived as "gut-feeling" (Fenton-O'Creevy et al., 2012). However, it is also shown that this influence of affective processes on user behavior is neither exclusively good nor bad (Bradley and Lang, 2007; Russell, 1980). For example, the relation of arousal and performance is approximated using an inverted U-shaped curve with a user-specific optimum, rather than a straight line (Yerkes and Dodson, 1908).

Relation B is based on a psychophysiological principle stating that there is a bidirectional causal relation between a user's physiological and perceived emotional state—consciously as well as unconsciously (Green et al., 1970; Walla and Panksepp, 2013). Whereas the effect of the emotional state on the physiological state might appear intuitive to most people based on their own experience (e.g., being stressed increases one's heart rate and respiration), research has also shown that changes in the perceived emotional state (e.g., using emotion regulation strategies) can change one's physiological state (Gross, 1998; Thompson, 1994).

Relation C refers to the effect of the user's current environment on their physiological and perceived emotional state, as well as their relation. User environment comprises all integral and incidental influences to which a user is exposed. Integral refers to influences that are directly induced by the main function of the environment, such as time pressure, technostress, and information overload (Adam et al., 2015; Riedl et al., 2012, 2013). Whereas incidental refers to influences that are induced by seemingly irrelevant aspects of the environment, such as temperature, colors, and interface design

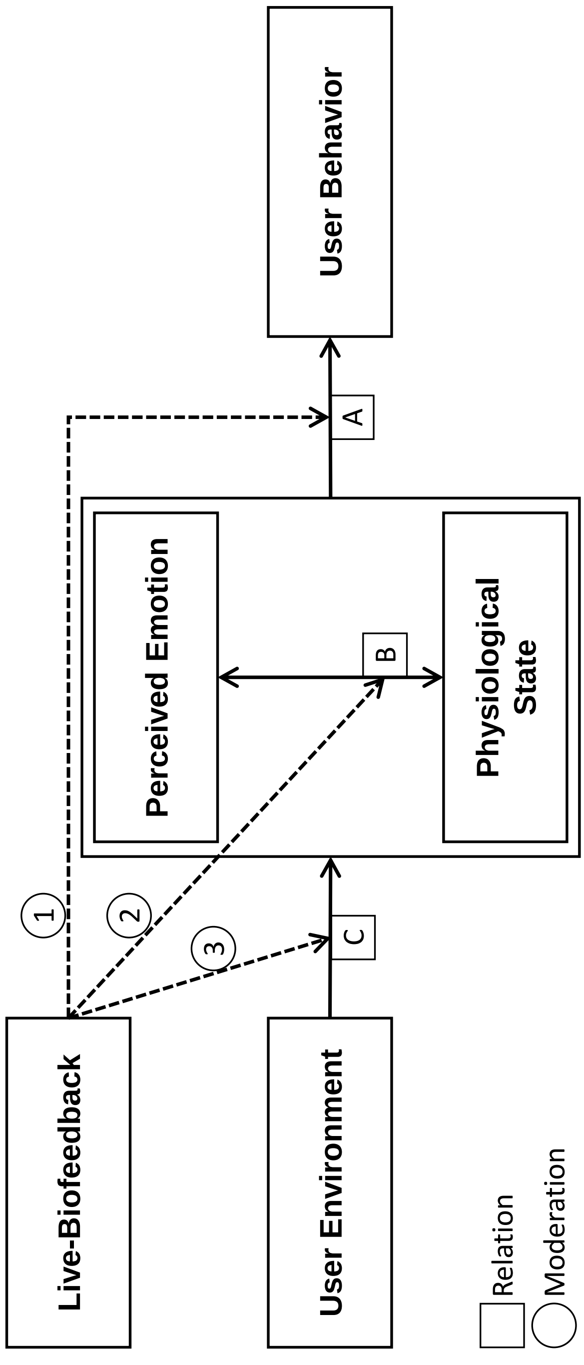


Figure 5.3.: Integrative Theoretical Framework on LBF.

elements (Hawlitschek et al., 2016; Riedl et al., 2011; Storey and Workman, 2013, 2014). Of course, LBF itself could be considered as part of the user's environment. But, as the framework focuses on understanding LBF, we explicitly model LBF and its moderating influences in separately to the user's environment.

Moderating Influences of Live-Biofeedback on Concepts

Based on the integrative literature review, we identify three general moderating influences of LBF that are investigated in the literature. These moderating influences are conceptualized as moderation 1 to 3 in the framework in Figure 5.3. In the following, we illustrate concepts on how LBF can moderate the relations of the above described framework . Moderation 1 refers to the moderating influence of LBF on the relationship between the user environment and affective processes. For instance, time pressure can instigate higher levels of emotional arousal in user, but LBF can help users to mitigate this influence. Moderation 2 refers to the interplay of changes in the physiological state and the perceived emotional state. In contrast to moderation 1, these changes have already materialized (in terms of perception and/or physiology), but might not be reflected in the corresponding physiological processes and/or perception. For instance, LBF can help users to become aware of increased arousal levels, and hence strengthen the relationship between the physiological state and the perceived emotional state. Finally, moderation 3 refers to how LBF can influence the relationship between affective processes and user behavior. For instance, previous research has shown that users tend to behave impulsively when they experience higher levels of emotional arousal (Sanfey et al., 2003). With LBF, users can be supported in reappraising the situation and avoid arousal to flash over on user behavior (Astor et al., 2013).

Importantly, it should be noted that moderation 1 to 3 are not mutually exclusive. Introducing LBF can have simultaneously or over time varying effects on multiple relations. The following section provides the result of the literature review, showing an overview of the existing LBF literature, that is structured along the above introduced integrative theoretical framework and the moderating influences of LBF.

5.3. Literature Review

The results of the literature review are structured along the relations and moderations of the above described integrative theoretical framework. The review follows the approach of Webster and Watson (2002).

5.3.1. Methodology

In order to define the boundaries of our literature review, we focus on publications concerning the following criteria:

- *Live-biofeedback*: Included are publications that apply online processing and immediate feedback of a user's neurophysiological data. This excludes offline and post-hoc processing of neurophysiological data, which might also be used to provide biofeedback, but does not provide the feedback while a user is in the situation in which the bio signals are recorded.

- *Healthy individuals*: Since LBF has roots in therapeutic medicine, many existing LBF publications are concerned with the effect of LBF in regard to health related issues. Due to the possible influence that health issues might have on the effect of LBF and the unknown generalizability for healthy users, we focus on LBF publications where users are healthy and not included into a study because of a given condition, i.e., where users have no prior record of measurement related health issues.

- *Non-clinical environments and consumer-grade sensors*: Due to the need for physiological measurement devices (i.e., sensors), the environment of LBF publications is often set in hospitals and medical centers. Such environments can be unfamiliar or even uncomfortable for users and, therefore, they can induce uncommon behavior. As for IS research, we focus on IS related environments that are more familiar to the users and their environments in which they use IS. Therefore, we focus on publications that are set in non-clinical environments. This also applies to sensors that require a very unfamiliar environment or that are not accessible to common users (i.e., consumers). For examples, we exclude full body functional Magnetic Resonance Imaging (fMRI) and Magnetic Resonance Tomography (MRT), which are too costly and unfeasible to operate for common users.

- *LBF-focused publications*: In order to research LBF, it is necessary to have appropriate tools and methods to create a working LBF implementation, e.g., the human-computer interface. Although creating an LBF system requires research related to LBF (e.g., refining sensors, recording and processing neurophysiological data, or interpreting and distinguishing user states), we only include publications that focus on the effect and use of LBF. We do not include research focusing on related research question, although, their results are important for improving LBF implementations and making them, for example, smaller, less costly, and more accurate.

- *IS Literature and IS related literature*: Although LBF is a multi-discipline research area, we focus on IS based literature. As the combination of IS and LBF is the focus of this paper, we do not include, for example, medical research outlets, as their focus predominantly is on the medical use and impact of LBF.

We conducted individual keyword searches using the keywords: *feedback* in combination with either *bio*, *neuro*, or *physi*. The keywords where used in combination with wildcard characters in order to also allow word combinations, such as *bio*logical, *physi*cal, and *physi*ological. The keywords are selected to represent related but generic terms in order to avoid temporarily popular buzzwords that are only used recently (Levy and Ellis, 2006). As the keywords are very generic, we received a broad list of results from the search that also included related but not relevant publications, such as NeuroIS publications including traditional feedback. Therefore, we additionally filter the search results manually into LBF relevant and not relevant. The search was done on title, abstract, and keyword fields (or the available subset of these fields) of the publications and the timeframe (i.e. available volumes) was not restricted. We selected the 53 major IS journals (i.e., ranked A* and A by the ACPHIS Ranking) and the proceedings of the 10 (affiliated) conferences proposed by the Association for Information Systems (AIS).

Reviewing the search results of these major IS outlets, we find that there are yet only few publications focusing on LBF—as initially expected. The search in the major IS journals returned 92 publications that matched a keyword, of which only 10 are relevant to LBF. Searching the selected IS conferences returned 13 publications matching a keyword and 2 relevant to LBF. We further broadened our search scope to other applicable IS research outlets (Webster and Watson, 2002). To identify applicable IS research, we match the above listed definition of LBF to the five major IS research streams (Banker and Kauffman, 2004). The HCI research stream is identified to be most compatible with LBF. Therefore, we include the major HCI-outlets (journals and conferences) into our search while keeping our defined search criteria. An overview of all outlets that were included in our search is provided in Table B.1. An exhaustive overview is provided in Appendix C.

Using the search results, we now describe the moderating influences of LBF indicated in Figure 5.3 in more detail. The found publications are classified according to their corresponding moderations 1 to 3 as depicted in Figure 5.3. An overview of all classified publications is provided in Tables 5.2 to 5.4.

5.3.2. Moderations

Moderation of the Impact of Affective Processes on User Behavior

Moderation 1 refers to the concept of consciously taking LBF information into account while being in a given context in order to actively alter one's own behavior. Here, LBF is used as an additional source of information, in addition to exciting context-specific sources, that provides the user access to their physiological and perceived emotional state, e.g., using a traffic light-like indicator in a financial trading environment to indicate the user's current stress level (Fernández et al., 2013). The LBF information can then be used to consciously reflect and analyze one's behavior and potentially avoid affect-driven biases, which are induced by the physiological or perceived emotional state. In the case of decision-making, this is often referred to as System 1 (fast and affect-driven) and System 2 (slow and consciously reflected) decisions (Kahneman, 2011; Stanovich and West, 2000). However, as user's ability to simultaneously self-monitor and attempt cognition-complex tasks is limited (Baumeister et al., 1998; Muraven and Baumeister, 2000), LBF is used to facilitate self-monitoring. Therefore, the main scope of moderation 1 is not to directly influence a user's physiological and perceived emotional state but to provide self-monitoring assistance.

Based on the existing literature, we find that moderation 1 is often applied in two ways: i) as a support system that is added to an existing environment and ii) in playful gaming application as a game enhancement. In case of using LBF as a support system, LBF is either used to support the user in changing their behavior to be more effective

Table 5.1.: Overview of searched outlets.

A*-ranked IS Journals
ACM Transactions on Computer-Human Interaction; Decision Support Systems; European J.o. IS; Information and Management; Information and Organization; IS Journal; IS Research; J.o. Information Technology; J.o. Management IS; J.o. Strategic IS; J.o. the Association for Information Science and Technology; J.o. the Association for IS; Management IS Quarterly

A-ranked IS Journals
Applied Ontology; Australasian J.o. IS; Behaviour and Information Technology; British J.o. Educational Technology; Business & IS Engineering; Communications of the ACM; Communications of the Association for IS; Computers and Security; Data and Knowledge Engineering; DATA BASE for Advances in IS; Electronic Commerce Research; Electronic Markets - The Int. Journal on Networked Business ; Enterprise IS; Group Decision and Negotiation; Human-Computer Interaction; IBM Systems Journal; Information and Software Technology; Information Communication and Society; IS; IS Frontiers; Information Technology and People; Int. J.o. Cooperative IS; Int. J.o. Electronic Commerce; Int. J.o. Information Management; Int. J.o. Medical Informatics; Internet Research; J.o. Computer IS; J.o. Global Information Management; J.o. IS; J.o. Information Technology Theory and Application; J.o. Knowledge Management; J.o. Organizational Computing and Electronic Commerce; J.o. the American Medical Informatics Association; Knowledge Management Research and Practice; Knowledge-Based Systems; MISQ Executive; New Technology, Work and Employment; Personal and Ubiquitous Computing; Scandinavian J.o. IS; The Information Society

Major IS Conferences
Int. Conf. on IS; Americas Conf. on IS; European Conf. on IS; Pacific Asia Conf. on IS; Int. Conf. on IS Development; Int. Conf. on Mobile Business; Mediterranean Conf. on IS; Wuhan Int. Conf. on e-Business; Australasian Conf. on IS; Int. Conf. on Information Resources Management

HCI and related IS Outlets
HIC Int. Conf.; Int. Conf. on Engineering Psychology and Cognitive Ergonomics; Int. Conf. on Universal Access in Human-Computer Interaction; Int. Conf. on Virtual, Augmented and Mixed Reality; Int. Conf. on Cross-Cultural Design; Int. Conf. on Social Computing and Social Media; Int. Conf. on Augmented Cognition; Int. Conf. on Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management; Int. Conf. on Design, User Experience and Usability; Int. Conf. on Distributed, Ambient and Pervasive Interactions; Int. Conf. on Human Aspects of Information Security, Privacy and Trust; Int. Conf. on HCI in Business, Government and Organizations; Int. Conf. on Learning and Collaboration Technologies; Int. Conf. on Human Aspects of IT for the Aged Population; Special Interest Group on Human-Computer Interaction

Abbreviations:
IS = Information Systems, J.o. = Journal of, Int. = International, Conf. = Conference

or physically active (e.g., Landau and Leonhardt, 1988; Murray et al., 2013; Nishimura et al., 2007; Taylor et al., 2013), or LBF is used to indicate a user's state to another user (e.g., an instructor) in order enable better cooperation (e.g., Tan et al., 2014; Walmink, Wilde, and Mueller, 2013). In case of using LBF in playful gaming, LBF is used to increase a user's engagement with a game (Kuikkaniemi et al., 2010; Nacke et al., 2011) or to use LBF as an unique game element (Walmink et al., 2013).

Moderation of the Interplay between the Physiological State and the Perceived Emotional State

Moderation 2 refers to a user's ability to perceive one's current physiological state (i.e., interoception (Vaitl, 1996)) and one's emotional state (i.e., introspection (Boring, 1953)). This ability is highly individual (Barrett et al., 2001) and can depend on factors such as a user's physiology (Verlinde et al., 2001), experience (Fenton-O'Creevy et al., 2012), and emotional regulation capabilities (Peira et al., 2014). Users without any training or experience have been shown to be less able in accessing their physiological and perceived emotional state (Epstein and Blanchard, 1977; Sze et al., 2010). However, it has been shown that it is possible to train this ability (Cochran, 2011; Jercic et al., 2012; Sutarto et al., 2010). Therefore, the main scope of moderation 2 is to assist users in training and enhancing their self-monitoring abilities.

Existing literature shows that often either serious or playful games are used to address moderation 2. Whereas serious games are themed to have similarities to existing IS environments, playful games are set in imaginary environments that are unattached to real-world IS environments. In both types of games, LBF is used to control the game (e.g., LBF used as user input) (Antle et al., 2015; Jirayucharoensak et al., 2014). Additionally, some games also use LBF to change the mechanics of the game itself (e.g., game difficulty or properties of the game character) (Al Rihawi et al., 2014; Jercic et al., 2012; Walmink et al., 2013). Another approach found in literature to address moderation 2 is by using support systems that are used in (often) dedicated training sessions (Hao et al., 2014; Harris et al., 2014; Umek et al., 2015). Also, as moderation 1 to 3 are not mutually exclusive, moderation 2 is found as effect that unfolds over time, in studies focusing on moderation 1. Here, users learn over time to control their state and better respond to the provided LBF (Landau and Leonhardt, 1988; Murray et al., 2013; Walmink et al., 2013).

Table 5.2.: Overview of classified LBF publications.

1. Authors (year)	Outlet	Task, Description	LBF Moderation 3	LBF Moderation 2	LBF Moderation 1	Additional Neuro-Adaptive component	LBF integrated in task	Domain	NeuroIS Method ECG	EDA	EEG	Pleth	EMG	Resp	other	Feedback type Visual	Auditory	Other
Al Rihawi et al. (2014)	SIGCHI	Game trains subjects to relax during gameplay		x		Game property	x	Playful Games						x		x		
Antle et al. (2015)	SIGCHI	Improve self-regulation abilities in children (relaxation/anxiety & focus/attention)		x			x	Serious Games			x					x		
Astor et al. (2013)	JMIS	Serious game for emotion regulation training in a financial decision making context		x		Game difficulty	x	Serious Games	x							x	x	
Hao et al. (2014)	SIGCHI	Teach people how to regulate their emotions more effectively in stressful situations		x				Support System			x							LED wristband
Harris et al. (2014)	SIGCHI	Tool for stress management by respiration control		x				Support System						x			x	
Jercic et al. (2012)	ECIS	Serious game for emotion regulation training in a financial decision making context	x	x		Game difficulty	x	Serious Games	x							x	x	
Jirayucharoensak et al. (2014)	SIGCHI	Training to enhance cognitive performance in older adults		x				Serious Games			x					x		
Koutepova et al. (2010)	SIGCHI	Enable longer immersion for players of video games	x			Game property	x	Playful Games	x	x						x	x	
Kuikkaniemi et al. (2010)	SIGCHI	Influence of implicit and explicit biofeedback on video game experience	x		x	Game property	x	Playful Games		x			x	x		x		
Kuipers et al. (2016)	Int. Journal of Medical Informatics	Change lifting behavior and transfer techniques to prevent lower-back injurie			x	Game property	x	Playful Games							Posture	x	x	
Landau and Leonhardt (1988)	SIGCHI	Shape a working-posture at the computer terminal for optimal relaxation		x	x			Support System					x					verbal hint from instruction
Lux et al. (2015)	ECIS	Financial decision making in a continuous double auction	x		x		x	Serious Games	x							x		

Table 5.3.: Overview of classified LBF publications (continued).

1. Authors (year)	Outlet	Task, Description	LBF Moderation 3	LBF Moderation 2	LBF Moderation 1	Additional Neuro-Adaptive component	LBF integrated in task	Domain	NeuroIS Method ECG	EDA	EEG	Pleth	EMG	Resp	other	Feedback type Visual	Auditory	Other
Matthews et al. (2015)	SIGCHI	System to assist with relaxation techniques	x				x	Support System		x								ambient lighting
Moraveji et al. (2011)	SIGCHI	Peripheral paced feedback to influencing respiration	x				x	Support System						x		x		
Moraveji et al. (2012)	SIGCHI	Augmenting respiration self-regulation without cognitive deficit	x				x	Support System						x		x		
Murray et al. (2013)	HCI International	Real-time avatar feedback to induce changes physical behavior		x	x		x	Support System							(Accel.)	(x)		
Nacke et al. (2011)	SIGCHI	Using direct and indirect physiological control to enhance game interaction			x	Game property	x	Playful Games	x	x		x	x	x	Audio, Eye Tracking, Temp.	x		
Nishimura et al. (2007)	HCI International	Physiologic system interfaces for improving operator effectiveness	x		x		x	Support System							fNIR			Tactile
Reitz et al. (2012)	SIGCHI	Creates a more personalized gaming experience and provides additional input modalities	x			Game property	x	Playful Games	x	x						x		
Sas and Chopra (2015)	Personal and Ubiquitous Computing	Wearable system for training mindfulness state		x			x	Support System			x						x	
Schnädelbach et al. (2010)	SIGCHI	Linking physiological data and the fabric of building architecture	x				x	Support System	x	x				x		x	x	
Schnädelbach et al. (2012)	AMCTCHI	Physiologically driven adaptive architecture	x				x	Support System	x	x				x		x	x	

Table 5.4.: Overview of classified LBF publications (continued).

1. Authors (year)	Outlet	Task, Description	LBF Moderation			Additional Neuro-Adaptive component	LBF integrated in task	Domain	NeuroIS Method							Feedback type		
			3	2	1				ECG	EDA	EEG	Pleth	EMG	Resp	other	Visual	Auditory	Other
Snyder et al. (2015)	SIGCHI	Exploring personal and social implications of ambient display of biosensor data	x	x			x	Support System		x								ambient lighting
Tan et al. (2014)	SIGCHI	Partner biofeedback to improve video-mediated collaboration			x		x	Support System		x		x		x		x		
Taylor et al. (2013)	SIGCHI	Posture training with real-time visual feedback			x			Support System							Posture	x		
Tennent et al. (2011)	SIGCHI	Using breath control as an interaction medium for gaming	x			Game property	x	Playful Games						x		x		
Umek et al. (2015)	Personal and Ubiquitous Computing	Sports training system for proper movement patterns		x			x	Support System							Accel.		x	
Vidyarthi et al. (2012)	SIGCHI	Breath related adaptation of ambient sounds for cultivating mindfulness	x					Support System						x			x	
Vidyarthi and Riecke (2013)	SIGCHI	Designing for an immersive experience of meditation by connecting respiration to music	x					Support System						x			x	
Walmink et al. (2013)	SIGCHI	Digitally enabled real-world sword-fighting game		x	x	Game property	x	Playful Games	x					x	Accel., Posture			LED on hat
Walmink et al. (2013)	SIGCHI	Displaying heart rate data to support social exertion experiences			x		x	Support System	x									bicycle helmet

Moderation of the Impact of the User Environment on Affective Processes

Moderations 3 refers to the effect that LBF has on the user's perception of the environment. As a user "is never *without* being in some emotional state" (Zajonc, 1984, p. 121), LBF can influence the effect the environment has on a user. Changes in one's state can also be triggered by the environment itself—even as a cognition-free reaction, i.e., without the user deriving meaningful information. Here, it is the effect of LBF on the user's affective processes without the user focusing on LBF information. Therefore, LBF can to some degree influence affect-driven processes (e.g., System 1 decision-making), comparable to psychological effects such as social facilitation (Zajonc, 1965). For example, even when users paid little or no attention to the LBF (Jercic et al., 2012), the LBF showed inaccurate information (Chittaro and Sioni, 2014), or the LBF was included without further introduction (Schnädelbach et al., 2012), the user's affective processing can be influenced by the mere presence of LBF. Therefore, the main scope of moderation 3 is to assist the user's affective processing of environmental influences.

Inspecting the existing literature, we find publications addressing moderation 3 often use LBF in support systems that are included in the user's environment and that influence the user's ambiance to reduce stress, improve relaxation, or increase creativity, for example, by using lighting and sounds (Matthews et al., 2015; Moraveji et al., 2011, 2012; Schnädelbach et al., 2010, 2012; Vidyarthi et al., 2012). Further uses of LBF to address moderation 3 are playful games, where LBF is used to create a more immersive experiences (Koutepova et al., 2010; Kuikkaniemi et al., 2010; Reitz et al., 2012). Additionally, moderation 3 is found as an effect over time in literature focusing on moderation 1 or 2, and serious game or support system (Jercic et al., 2012; Lux et al., 2015; Matthews et al., 2015; Nishimura et al., 2007).

5.4. Discussion and Outlook

5.4.1. Discussion and Limitations

The results of the literature review show that LBF has great potential for future IS research and real-world applications, such as support systems. In IS research, the increasing availability of sensors (i.e., affordable and easy to use) inspires researchers to include LBF as well as NeuroIS in general into more and more of their research studies—based on the increasing number of such publications. Especially, since adding physiological data to a research study acts as an addition to existing tools and methods. Here, researchers are supplied with additional and potentially new approaches to address their research questions or even revisit previous research questions. For the case of LBF, however, research studies are still sparse. Although, single studies provide evidence of the effect of LBF on behavioral biases, as listed in the previous sections, a structural research approach has not yet been published. Therefore, the proposed integrative theoretical framework can provide assistance for future researchers. The framework shows three different, yet not excluding, moderations of LBF on users in the context of decision-making. While a comprehensive analysis of all LBF moderations is yet to come, looking at existing literature, it is feasible to assume that users can greatly benefit from adding LBF into their existing decision-making process. For example, by including LBF as an addition to their "Adaptive Toolbox" (Gigerenzer and Selten, 2002), LBF can provide addition information that previously was not available—especially, live and instant at the time when a decision has to be made.

However, using LBF in the context of decision-making can have some challenges. First, the implementation of the LBF. Although, as state before, LBF can be used as an addition to existing IS and is, therefore, easier to integrate than other comparable Neuro-Adaptive IS. Yet, LBF still requires a broad understanding of handling physiological data (i.e., their collection, processing, and interpretation) as well as (some) additional operational costs. But, especially in the case of decision-making in a financial context, the additional information provided by LBF can be the little edge that is required to beat one's competition (Fenton-O'Creevy et al., 2012; Seo and Barrett, 2007). Second, LBF requires constant use and (in some cases) additional training in order for the user to fully benefit from the LBF. But, as decision-makers are already often on a tight schedule, adding LBF to their daily routine might seem as an additional work load. This is also the most common problem reported in the existing literature, which focuses on using LBF in field studies with real experts (Cochran, 2011). But, similar to the previous stated additional costs, investing time in LBF and LBF training can create great benefit for a user over time. Especially, as several publications suggest, using LBF over time changes one's need for extra LBF support. This means, that, over time, the additional time required for LBF and LBF training can be reduced without the loss of already acquired LBF capabilities and their benefits. Third, the use of physiological data requires a high level of data protection and security as physiological data is one of the most personal data. If the data is handled (i.e., collected, analyzed, and store) by the users themselves, it has to be ensured that the data and the analysis results are properly secured. As the data reveals very sensitive information about the users, their behavior, and potential "weaknesses," the data is highly attractive to competitors or people with bad intentions. If the data is handled by a third party, for example, an employer, the data has to be also as secure as state before, but the third party now has a very high level of responsibility of protecting the data (Hubbard et al., 2016; Solon, 2015). Similar to social security information, physiological data and their analysis results can have a monetary value and must only be passed on with the permission of the corresponding user. Hence, the third party must protect the data and prevent their loss in the interest of the users. Existing data protection laws already cover physiological data to some extent, for example, in the context of medical data use. But, using physiological data in IS may create the need for new and explicitly created data protection laws in IS.

5.4.2. Outlook and Future Research

In order to fully benefit from LBF, we further need to better understand its effects and use in IS by systematically researching LBF. Future research can focus on several of following areas but, certainly, are not limited to them.

First, the collection of physiological data. As LBF and the use of sensors to collect physiological data is based on the medical use, the collected data usually very precise, very dense, and is recorded at a high frequency. However, for the non-medical use in IS, the collected data might not need at such a high quality. If, for example, data is recorded for an entire work day and for decisions that are made in minutes, recording at a millisecond rate might not be necessary. Further, the location of the sensors. As in medicine, sensors are mostly applied to record data while the user is not doing any activity. In IS, the users still have to complete their daily task. Here, the sensors must be as unintrusive as possible in order for the user to not be distracted. Therefore, one area of research can focus on optimizing sensors (i.e., their location or integration in other devices) and on the necessary data quality that is required to still produce interpretable results.

Second, the processing of physiological data. As introduced in Chapter 4, processing physiological data has a high complexity. This complexity results from the immense variety of different measurements and their appropriateness to a given context. Derived from medical practice and research, every measurement of a human body's physiological activity can be assessed using several different approaches. In ECG data, for example, the measurements range from simple calculation of beats per minutes (BPM) to computational complex frequency and special geometrical analysis. In addition, since those measurements are mathematical transformations of electrical signals, they also allow for a multitude of parameterizations. Although, some research has already focused on this area (e.g, Schaaff and Adam, 2013; Müller et al., 2016), many questions are still unanswered, such as introducing multi-modal models (D'mello and Kory, 2015).

Third, the LBF output. As previously stated, the LBF output can consist of a single or multitude of feedback outputs, such as visual, auditory, and tactile. Which single or which combination of the possible forms of feedback is most useful for a given context, however, is not yet clear. This also includes the question, whether and how the feedback should be integrated to maximize its effect. For example, the feedback could either be included into existing interfaces, could be added as dedicated interfaces, or could even be added as dedicated devices (i.e., Djajadiningrat et al., 2009).

Fourth, the interaction of personal attributes. Although, literature suggest that LBF effects most people, it is not clear to what extent personal attributes interact with the effect of LBF in a given context. Personal preferences, experience, physical fitness, skills, and emotion regulation capabilities are factors that could interact with LBF. Such factors could, in the future, be considered when users are using LBF for the first time, e.g., by providing them with a different form of feedback output, adjusting specific thresholds, and varying their LBF training.

Five, the effect of LBF on behavior biases in a given context. In this chapter, we focused on LBF in the context of IS research and its potential for building LBF support systems. While support system for decision-making are the most prominent example for LBF support system in this chapter, there are further possible applications areas. For example, technostress, the stress induced by using IS (Riedl et al., 2012; Riedl, 2013), could also benefit from LBF—yet having a different desired behavior. In this context, as well as decision-making and other possible contexts, LBF can help users to influence their behavior to mitigate behavioral biases. However, it is not yet clear, which feedback is best used in which context and at which point in time in the given context. For example, in decision-making in electronic auctions, literature showed that being too aroused could lead to overbidding. But, being too little aroused could result in being not attentive enough and bidding less than necessary—also an undesired bidding behavior.

Six, the interaction of LBF in a group environment. Most environments in which LBF is researched focus on collecting physiological data from a user and providing the same user with the resulting LBF. However, LBF can also provide valuable information to a second user, for example, a team member or a supervisor. In case of team members, they could use their partner's LBF to ensure or second-guess their partner's decision or action. In case of a superior, the LBF could assist in monitoring employees to prevent them from bad decision due to over arousal or fatigue. Further, merging and aggregating LBF on a group level could provide a supervisor with additional information of multiple users and show a general mood or sentiment of a team. At the same time, the information of individual users remains private. However, how well others perceive such foreign LBF (fLBF), how it is best presented, and how well others are able to interpret this foreign LBF is not yet clear.

Seven, the mid and long term effects of constantly using LBF. As indicated in the literature review, using LBF over a longer period of time might change the type of LBF moderation. The literature provides evidence that their might be a LBF live-cycle, which users pass through over time. Going from moderation 1 to 3, LBF could change the user's behavior in the desired direction. Starting with direct and obvious feedback (moderation 1), then internalizing the effect of the LBF (moderation 2), and, finally, perceiving LBF only passively (moderation 3). How fast or slow this transition is possible, what contexts this is possible, and whether all users are capable of this, is also to be research in the future.

5.4.3. Example: A NeuroIS Platform for Lab Experiments

In order to provide a real-world example on how LBF and NeuroIS in general can be applied in IS research, in to following, a NeuroIS platform for laboratory experiments is introduced. The platform was developed at the Karlsruhe Institute of Technology (Germany) especially for the purpose of utilizing physiological data in IS research. The platform supports researches in creating, conducting, and analyzing laboratory experiments that include physiological data, even in a multi-participant and multi-sensor environment.

Problem Identification and Motivation

NeuroIS research necessitates the collection of high quality empirical data (Dimoka et al., 2012). In particular, research in this domain necessitates the collection of psychophysiological and neuroimaging data synchronized to a subject's current context. Here, context refers to the environment and the behavior of the observed subject, e.g., decisions during an auction, answers on a questionnaire, or the time to complete a control task. Due to the controlled environment, many researchers use lab experiments to conduct their studies and collect the above described data (Falk and Heckman, 2009).

Software used in these lab experiments, either third-party or customized software, often suffers from a number of limitations, such as (i) a limited set of functionalities, both for the user interface and the experimental structure, (ii) data collection and storage being spread over several different tools, which results in data synchronization problems and time consuming post-experiment data cleaning, (iii) being limited in subject size or possibilities in subject interaction, (iv) requiring to learn new or proprietary programming languages in addition to heavy programming effort, (v) no extensibility to handling emerging and changing software and hardware, e.g., new operating systems or new bio sensor technology, (vi) missing flexibility to handle requirements of experimental economists, IS researchers, or to meet future requirements, such as integrating physiological data to research technostress (Riedl et al., 2012).

Objectives of the Solution

Following a design science approach Peffers et al. (2007), we next define broad objectives of a possible solution to address the problems stated above.

- Facilitating the creation of lab experiments by reducing development time and cycles
- Facilitating individual and group interactions in a controlled lab setting
- Integrating measurements of bio sensors and logging of physiological data specific to subject events
- Ease of event logging and data storage, enabling experiments to scale in time and subject size

- Meeting emerging technical requirements in the field of IS research and experimental economics

Objectives of the Solution

To address these objectives, we herewith present a Java-based platform, which provides functionalities necessary to run NeuroIS lab experiments while, at the same time, offering flexibility to adapt to experiment specific requirements. The platform implementation is inspired by Smith (1982) definition of an experimental system. In combination with the integration of bio sensors, the platform can be used in many research disciplines, which seek to apply a NeuroIS approach, e.g., design science (vom Brocke et al., 2013), biofeedback (Jercic et al., 2012), consumer research (Koller and Walla, 2012), and educational software (Chintalapati et al., 2010). The platform's support for experiments with multiple and simultaneously interacting subjects, for group or market experiments, offers numerous possibilities for NeuroIS research.

The platform's software architecture is divided into two parts (see Figure 5.1): a built-in part (*core components*) and a customizable part (*experimental design* and *bio sensors*). The core components, which are provided by the platform, form the robust foundation. They handle, for instance, client-server communication, database logging with client and server timestamps on millisecond precision, and the management of experimental sessions, i.e., all the required building blocks essential to almost all lab experiments. Also provided by the core components is an internal database, which makes the use of a dedicated database server optional.

On top of the core components, the customizable parts are implemented by the researcher. Both customizable parts, the experimental design and bio sensors, are based on the idea of modules, i.e., they are developed independently and added to the core component as needed. First, the experimental design which defines the actual experiment. Here, the researcher implements all elements and "rules" of the experiment, e.g., the experimental procedure, the matching of subjects and groups, and the options for subjects to interact. The experimental design also defines the visualization of the experiment, i.e., the user interfaces, which are shown to the subjects. Since there are no restrictions to what Java elements can be integrated into the design of the user interfaces, all elements can be included from simple elements, such as images and videos, to more complex elements, such as dynamic real-time charts and the integration of websites

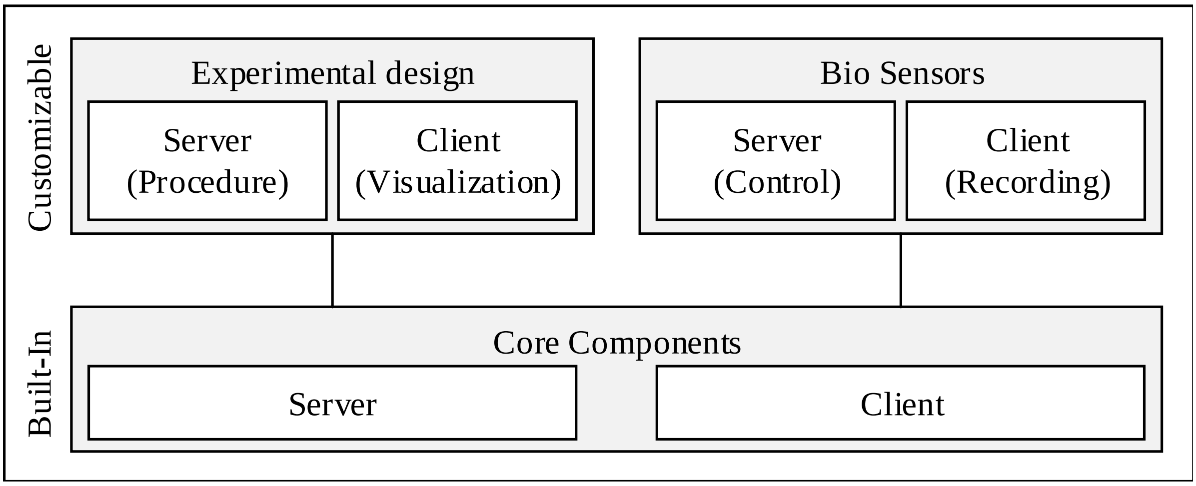


Figure 5.4.: Basic architecture of NeuroIS platform.

through a built-in web browser element.

The second part, which is implemented by the researcher, is the bio sensors. This optional part is used to integrate support for various bio sensors into the platform. To facilitate the integration, the platform provides a general framework for handling bio sensors, which can be adapted by the researcher when integrating support for his or her specific bio sensor. This general bio sensors framework provides functionalities for a centralized control in order to manage and operate all connected bio sensors simultaneously—especially useful in experiments with multiple subjects. These provided functionalities include starting and stopping data recordings, defining storage strategies, and monitoring the bio sensors' connection and overall data quality. As a result, using bio sensors in lab experiments becomes less time consuming, since bio sensors do not have to be setup or monitored individually. In addition, the recorded data is available instantaneously within the platform and can therefore be included into the experimental design itself, e.g., by using physiological data to create a real-time biofeedback element in the user interface.

Demonstration

Next, as part of the demonstration, and to observe how well the developed artifacts solve the above mentioned problems better, we present two use cases that were implemented using the proposed platform. Use case (1) implements a single-subject auction experiment, whereas use case (2) implements a multi-subject auction experiment. Both experiments were conducted with different sets of bio sensors.

Use case 1: Measuring interplay of emotions and workload in auctions.
This use case is an auction experiment on 54 subjects wherein subjects' brain activity was recorded using a 32-channel electroencephalograph (EEG) along with their electrocardiogram (ECG) and skin conductance (SC) data. The platform enabled the interaction between each subject and 2 computer opponents in different auction types and conditions, namely ascending and descending auctions. The aim of the experiment was to understand how the IS constructs (arousal and workload) are influenced by the auction types and conditions, and how they in turn impact subjects' bidding behavior. By means of the platform, events of interest (such as information events, placing of bids, outcome, and regret information) were logged directly to the database along with client and server timestamps. Synchronously, triggers were added from the Java interface of the platform to the EEG data through suitable Java wrappers to perform system-level calls, and transmit the event trigger via parallel port, along with the timestamp information. In parallel, heart rate and skin conductance data were transmitted over Bluetooth, and stored on the local client

Use case 2: Investigating the influence of auction fever on bidding behavior in auctions.
The second use case was conducted with a total of 216 subjects where ECG, SC, and plethysmography data were recorded. During this experiment, nine subjects at a time competed in groups of three in multiple ascending auctions. For each auction, groups were automatically re-matched to achieve a perfect stranger matching. Before the experiment started, all subjects had to successfully complete a questionnaire on the experiment's instructions in order to ensure that they understood the upcoming events. Using the platform's built-in questionnaire capabilities, the experiment was set to wait for all subjects to complete the questionnaire and only then continue with the actual experiment. Next, subjects could choose an individual name and picture, which later was used in the experiment to show subjects their current competitors in the user interface. By choosing and implementing a between-subjects design, the experiment had a 2 $\times$ 2 full-factorial treatment structure. Using the platform's session manager, the sequence of treatments was set, such that all treatments were conducted equally often and that they were properly distributed over time to avoid, for example, time-of-day biases. The recorded events of interest were similar to those of use case (1), e.g., the placing of bids

and the auction outcome, in addition to the simultaneously recorded bio sensor data. Due to the high amount of data produced by the bio sensors during an auction, the data was first stored on each local client and then was moved automatically to a central storage location after all auctions were completed.

Evaluation

The initial evaluation of the presented platform shows that the experiments in both use cases were programmed with ease, conducted successfully, and enabled easy data handling post-experiment—hence, indicating the potential of this NeuroIS platform.

Also, the platform meets the previously defined objectives. Creating an experiment is less time consuming, since the necessary basic building blocks are already provided, and the well-known and widely available programming language Java is used for implementations. Researchers therefore can focus their attention on the design and calibration of their experiments, rather than spending time and effort on re-developing generic and existing software solutions, e.g., client-server communication. This provided client-server communication in particular allows researchers to create experiments where subjects can not only act individually, but also interact in group or market experiments with no additional overhead in the implementation. In combination with the integrated bio sensor functionalities, the platform facilitates measuring and logging of physiological data as well as context data of the conducted experiment. All this results in less effort spent for the collections, cleaning, and preparation of data, which reduces data errors and provides more time for the statistical analyses of interest. At the same time, since the platform is an open-source software project, any researcher can adapt the platform to meet new emerging requirements in his or her respected domain of research.

Additional evaluation was provided by presenting the platform to members of various departments at the Karlsruhe Institute of Technology (KIT). Thereby, valuable feedback was provided and incorporated into the implementation of the platform. As a consequence, as of today 15 studies (completed and on-going) already used the platform to implement their experiments. The range of research areas includes realms such as market design & behavior, applied economics, and consumer behavior.

Communication

The platform will be distributed as a pre-compiled version for instant use, where the application can be started either as a client or as a server, as well as a version including a ready-to-use development workspace for easy access to own implementations. The source code will be available as a version controlled repository, which can be downloaded, modified, and used to include community feedback, such as bug-fixes and new features. As examples, three implemented sample experiments will be provided. In addition, tutorials will be made available in the form of sample sensor setups, documentation of the architecture explaining core concepts, and documentation of source code where necessary. Technical support will be provided through commonly used tools, such as issue trackers and forum discussions. Finally, the importance of the artifact, its usefulness and originality, as well as several aspects of the design and architecture will be communicated through scholarly research publications.

Contribution

The presented platform serves as a stable prototype to implement experiments involving physiological measurements and strategic interactions. Following an iterative design science process, the next steps are to examine the existing requirements critically and redefine new ones, where necessary. Based on these, the available features will have to be further developed, incorporating feedback from NeuroIS researchers, and cater to the needs of a broader community of researchers to use the platform for their studies.

Finally, the presented software platform facilitates the conduction of NeuroIS lab experiments, which hopefully inspires researcher to employ NeuroIS experiments.

5.5. Conclusion

In this chapter, we reviewed and analyzed LBF in the context of IS research and its potential for building LBF support systems. In order to gain a better understanding of the systematical effects and potential of LBF as support system, this chapter provides a comprehensive literature review of the 53 major IS journals, the proceedings of the 10 (affiliated) conferences proposed by the Association for Information Systems (AIS), as well as the major HCI-outlets. Using the results of the literature review, we further derived and proposed an integrative theoretical framework. The framework introduces known relations of a decision-maker's environment, affective state, and behavior, and shows three proposed moderating influences of LBF. The chapter further shows potential uses for LBF in future research and applications (i.e., support systems) and concludes with an already existing example of a NeuroIS platform for laboratory experiments.

Part IV.

Finale

Chapter 6.

Conclusion and Future Research

Advances in sensor technology provide access to information hidden within human physiological data to more people than ever before. This valuable information is now used in research as well as in commercial applications. Especially, in economic decision-making, by increasing the understanding and providing support, human decision-makers can tremendously benefit from these newly available insights. The goal of this thesis is to better understand the decision-making process in electronic auctions by using a NeuroIS approach. Thereby, we utilize the understanding of human physiological data to provide support for decision-makers in the future. In this chapter, the main contributions of this thesis are summarized and several opportunities for using these contributions for future research are proposed.

6.1. Contributions

In Chapter 2, we seek to clarify the role of physiological arousal and its impact on bidding behavior in electronic auctions. Therefore, the phenomenon known as auction fever is investigated in an electronic auction environment using an ascending clock auction. The chapter addresses the following research question:

> **Research Question 1:** *Can physiological measurements provide evidence for the phenomenon of auction fever in ascending auctions?*

To investigate Research Question 1, a controlled laboratory experiment was conducted in which behavioral data (i.e., auction decisions) as well as physiological data (i.e., ECG) of the participants were recorded. A total of 240 students participated in 15 ascending clock auctions each. In all auctions, three participants competed simultaneously for a virtual good with a common value function. The analysis of the collected data revealed that physiological measurements used as an objective measurement provide significant evidence for the auction fever phenomenon. Bidders experience a higher degree of physiological arousal when time pressure is high and when bidders are competing with human opponents (rather than with computer opponents). An influence on bidding behavior was also shown such that bidders place higher bids when time pressure is high and that this effect is partially mediated by arousal. However, auction fever is no longer observable when bidders compete with computer opponents (rather than with human opponents). Further, it was shown that immediate emotions that are induced by seeing the auction outcome are significantly more intense when bidders win than when they lose. This means that the joy of winning is experienced stronger than the frustration of losing.

In Chapter 3, we continue the investigation to further the insights of Chapter 2. Using psychometric measurements instead of physiological measurements, this chapter complements the results of the previous chapter. By stimulating bidders' competitive arousal using avatars (stylized graphical representations of the bidders), the bidders' perception of competitive arousal is analyzed in order to identify the actual drivers of bidders' physiological arousal and the influence on decision-making. Therefore, the chapter addresses the following research question:

> **Research Question 2:** *How is competitive arousal perceived in the social competition of ascending auctions and what is its impact on bidding?*

To investigate the role of competitive arousal, a second laboratory experiment was conducted. The laboratory experiment is set in the identically controlled environment as the first experiment. Changes where made to the treatment structure (e.g., different degrees of time pressure and degrees of social competition) and the measurement for perceived arousal (i.e., psychometric measurements), which was collected using self-reported questionnaires. The student participants competed in four ascending clock auctions and were also grouped into three participants per auction, while competing for a virtual good with a common value function. The analysis of the experimental data confirmed the findings of the first experiment. This means that the results showed empirical evidence of a positive relationship between time pressure, social competition, bidders' perceived arousal, and bidding behavior. Analyzing the psychometric measurements, it was shown that social competition is the actual driver underlying the auction fever phenomenon. Thus, auction fever really exists—but only when bidders compete with human opponents (i.e., social competition).

In Chapter 4, we develop and demonstrate a methodological approach for selecting physiological measurements (i.e., features) for a given context. Physiological measurements provide insights into a decision-maker's affective processes, which have been shown to play an important role in determining decision-making in electronic auctions. However, existing literature does not provide an answer to which of the thousands of possible features that can be computed from physiological are particularly useful in predicting human behavior. Identifying useful features is important for gaining a better understanding of affective processes in electronic auctions and for building support systems, such as biofeedback systems. To this end, an evolutionary algorithm is applied in combination with either multiple linear regressions or artificial neural network models to select physiological features and assess their predictive power (i.e., usefulness). Using this approach, Chapter 4 addresses the following research question:

> **Research Question 3:** *How can evolutionary algorithms be used to select physiological features for predicting bidding behavior in electronic auctions?*

To investigate Research Question 3, the approach was developed and tested using ECG data and synchronously recorded auction decisions that were collected in the laboratory experiment of Chapter 2. The analysis of the results showed that the approach is able to select physiological features that can predict auction behavior. The approach robustly identified features that have constantly more predictive power than others. Whereas the parameters' selection type and window size did not show a significant impact in predictive power, using positive window offsets showed a significant difference in selection types (i.e., either milliseconds or heart beats). Therefore, the approach showed that selecting useful physiological features results is sensitive to the selected feature and that not all features provide the same predictive power. Also, the selection of physiological features is dependent on the context in which they are used and the definition of usefulness in this context. In the electronic auction context, using the presented approach can provide an additional insight into selecting physiological features that can create tremendous advantages.

In Chapter 5, we review and analyze Live-Biofeedback (LBF) in the context of IS research and its potential for building LBF support systems. LBF systems use a person's physiological data to create instant (i.e., live) feedback in the person's current context. The physiological data is measured using various and sometimes simultaneously used sensors, such as heart rate, skin conductance, and respiration. The feedback output can consist of a single or multitude of outputs, such as visual, auditory, and tactile. This feedback is then maybe used by the receiving person to achieve a desired behavioral change. Especially, in the context of decision-making in electronic auctions, LBF has been shown to promisingly reduce behavioral biases (cf. Chapter 5). This chapter thus addresses the following research question:

> **Research Question 4:** *How can Live-Biofeedback be used in NeuroIS research to support decision-making in electronic auctions?*

In order to gain a better understanding of the systematical effects and potential of LBF as additional support system, Chapter 5 provides a comprehensive literature review of the major IS journals, the proceedings of the (affiliated) conferences proposed by the Association for Information Systems (AIS), as well as the major HCI-outlets. All included sources were not limited by publication year. Using the results of the literature review, an integrative theoretical framework is derived and proposed. The framework introduces established relations (from literature) of a decision-maker's environment, affective state, and behavior. The framework further proposes three moderating influences of LBF. Then, the potential uses for LBF in future research and applications (i.e., support systems) is shown and an existing example of a NeuroIS platform for laboratory experiments is given. Therefore, the chapter makes three core contributions. First, we provide an integrative theoretical framework for LBF and how it can be integrated into IS research. Second, a systematic literature review of LBF in the IS research and related research areas is presented. Third, an overview of potential application areas for LBF in IS research and related reseach areas is introduced, as well as their potential for real-world applications.

6.2. Outlook

As the previous section provided an overview of the main contribution of this thesis, we now turn our attention to ideas for future research.

Improve physiological measurements and their context-related interpretation
Although, this thesis comprehensively investigates and analyzes decision-making in ascending electronic auctions using a NeuroIS approach, further research is required to complete our understanding of the affective processes that drive human behavior. Factors, such as different auction formats (e.g., sealed bid auctions and continuous double auctions), additional physiological measurements (e.g., pupil dilation and body movements), and changing stimuli (e.g., face-to-face video and voice audio) can provide complementing insights to the ones presented in this thesis. Especially, the measurement of arousal can benefit from having further measurement methodologies. Arousal is a state that can elicit changes in various parts of the human body. ECG and SCR.amp, as it was used in this thesis, are good proxies for arousal measurements but they are not the only measurement methods available. Other measurement methods, such as hormone levels or brain activity, also provide measurements for arousal but supply different time scales, precision, or level of intrusiveness when being measured. All of these aspects could add to the capturing of a user's current level of arousal. Also combining multiple arousal measures (i.e., a multi-factor arousal models), which has yet to be research, implemented, and verified, could outperform existing measurements.

Implementing prototypes of Neuro-Adaptive IS
The contributions of this thesis regarding the effects of arousal on decision-making in electronic auctions, in combination with additional existing literature, create a solid foundation for implementing real-world Neuro-Adaptive IS, such as Neuro-Adaptive decision support systems. Implementing and analyzing prototypes allows researches to evaluate, for example, design elements, user interfaces, or complex process flows using real users. Here, further research is necessary on topics, such as the users' acceptance of Neuro-Adaptive IS, the limits of Neuro-Adaptive IS (i.e., avoid information overflow, balance user autonomy and the control of the IS), data protection and security aspects (e.g., data protection laws), and, most certainly, the design as well as the effectiveness of such Neuro-Adaptive IS in a given context. Ultimately, research in this area can result in design guidelines, best practices, or even commercial applications.

Implementing and evaluating LBF support systems
As a specialized case of the previously stated implementation of Neuro-Adaptive IS

prototypes, the area of LBF support system in IS is still in its infant stage. Especially, the context of decision-making in electronic auctions, as it is presented in this thesis, creates a need for further, in-depth research on the topic of LBF in IS. To this end, the presented integrative theoretical framework (cf. Chapter 5) and the presented research outlook depict the opportunities and challenges for LBF in the future. Research question in areas, such as data processing, feedback format, interaction effects of personal attributes, and LBF's mid and long term effects, are only the beginning of a promising subfield of IS research—as well as commercial applications.

Apply the NeuroIS approach to decision-making in groups

Decision-making in electronic auctions is, in most cases, a single user context. In this context, only a single user is required to make a decision and, therefore, only the decision-making process of this user is in the focus of the research (as in this thesis). However, there are several decision-making contexts, where not one user but a group of users (i.e., two or more) are simultaneously involved in the decision-making process. Here, applying a NeuroIS approach can also provide additional information, yet, additional research questions have to be addressed first. Merging and aggregating physiological data on a group level provides information about multiple users' general mood or current sentiment. At the same time, the information of individual users remains private. But, how well others perceive this information, how it is best presented, and how well others are able to interpret this information remains to be addressed by researchers first.

Use of field experiments, professional users, and real-world applications

Building on the results presented in this thesis, transferring the insights of understanding and supporting decision-making in electronic auction into a real-world context offers great opportunities for researchers and practitioners. Researchers can test the robustness of the found insights in a real-world context. The real-world context often presents several restrictions that do not exist in research, such as restricted access to the users, software, and devices, reduced data quality, reduced effect size, interaction effects, or lacking user acceptance. Such challenges, however, can help research to refine existing models and theories and lead to improved research. On the other hand, practitioners can build on existing theories and models, such as the ones presented in this thesis, and create commercial applications.

Focus on non-decision-making and non-auction related research areas in IS
As the focus of this thesis is on decision-making in electronic auctions, many research areas that could benefit from contributions of this thesis are not considered. First, other research areas could benefit from applying a NeuroIS approach. The NeuroIS approach uses neurophysiological theories, methods, tools, and measurements to better understand the design, development, and use of IS. It is a complementary approach to existing research methods and, therefore, is not seen as a replacement. Including, for example, physiological data into research offers new insights into the inner processes of users that users often themselves cannot express. This adds to the understanding of user behavior in IS and provides numerous new opportunities, as stated above. Second, other research areas could benefit from using physiological data and, especially, LBF in support systems. Upcoming IS research areas, such as technostress, already use a NeuroIS approach to complement their research and gain insights into user behavior. Next, building support systems that automatically consider the gained insights can create support, minimize mistakes, or reduce costs for real-world users and their companies. This certainly holds also for other IS related research areas, such as HCI.

6.3. Summary

This Chapter presented the main contributions of this thesis and the emerging opportunities they offer to future research. First, we focused on understanding decision-making in electronic auctions using a NeuroIS approach. To this end, two laboratory studies were presented that analyze the phenomenon known as auction fever using a NeuroIS approach (i.e, Part II, consisting of Chapter 2 and Chapter 3).
Second, we focused on utilizing the previous gained understanding in combination with existing NeuroIS literature to support decision-making in electronic auctions. To this end, we introduce a working approach to select physiological measurements in a given context and further introduce an integrative theoretical framework for using LBF in IS and IS related research (i.e, Part III, consisting of Chapter 4 and Chapter 5).
Finally, we outlined several opportunities for using the contributions of this thesis for future research.

Part V.

Appendix

Appendix A.

Supplementary Material for Chapter 2

Participant Instructions and Questionnaires of Laboratory

This section list examples of instruction- and questionnaire documents that are used in the study of Chapter 2. There are the following documents listed: exemplary instruction for the "No social competition" and "Low time pressure" (NSC_LTP) treatment, emotion regulation questionnaire, bidding strategy questionnaire, and risk aversion questionnaire.

Teilnehmeranleitung

Sie nehmen an einem Experiment teil, bei dem Entscheidungsverhalten untersucht wird. Während des Experiments wird Ihr Hautleitwert, Herzrate und Puls aufgezeichnet und in der späteren Analyse mit ausgewertet. Sie können bei diesem Experiment ***echtes Geld*** verdienen. Wie viel Sie verdienen, hängt sowohl von Ihren Entscheidungen als auch von den Entscheidungen der Computeragenten ab. Kommunikation zwischen den Teilnehmern ist nicht erlaubt. Das Experiment besteht aus einer Folge von 15 Auktionen. Am Ende des Experiments erhalten Sie **15 Euro** zuzüglich der von Ihnen erwirtschafteten Gewinne und abzüglich der von Ihnen verursachten Verluste. In diesem Experiment wird in Geldeinheiten (GE) gerechnet. 10 GE entsprechen einem realen Geldbetrag von 2 EUR.

1. Aufbau und Ablauf einer Auktion

Bei jeder Auktion bieten Sie und zwei weitere Computeragenten auf ein fiktives Gut, welches zum Verkauf steht. Bei der Auktion wird ausgehend von einem Startwert von **25 GE** der Preis solange erhöht, bis nur noch einer der Bieter an der Auktion teilnimmt und damit das Gut erwirbt. Dieser Preis wird nach je **fünf Sekunden** um jeweils 1 GE erhöht, bis zwei der drei Bieter aus der Auktion ausgestiegen sind. Sie steigen aus der Auktion aus, indem Sie auf den Button **„Aussteigen“** klicken. Sobald zwei der drei Teilnehmer Ihrer Gruppe aus der Auktion ausgestiegen sind, ist die Auktion beendet und der verbliebene Bieter erwirbt das Gut für den dann gültigen Preis. Falls Sie aus der Auktion ausgestiegen sind, so erzielen Sie einen Nullgewinn. Sofern Sie der letzte verbliebene Bieter sind, so berechnet sich Ihr Ertrag dieser Auktion nach folgender Formel:

Ertrag = Wiederverkaufswert - Kaufpreis

Der Wiederverkaufswert des Gutes ist für alle Bieter **identisch**, ist jedoch vor und während der Auktion nicht bekannt. Der Wiederverkaufswert wird zufällig aus den Zahlen zwischen **46** und **95** gezogen nachdem die Auktion beendet wurde. Jede Zahl zwischen 46 und 95 hat dabei die **gleiche Wahrscheinlichkeit** gezogen zu werden. Das ist so als ob 50 Kugeln, die jeweils mit einer Zahl zwischen 46 und 95 beschriftet sind, in einer Urne abgelegt werden. Ein Zufallszug aus der Urne bestimmt dann den Wiederverkaufswert des Gutes dieser Auktion.

Der Gewinner der Auktion erhält den Wert des Gutes abzüglich seines Gebotes. Dieser Zusammenhang soll an einem Beispiel verdeutlicht werden. Nehmen wir an, Sie waren der letzte verbliebene Bieter und haben die Auktion mit einem Preis von 65 GE gewonnen und damit die Auktion beendet. Nun gibt es folgende Fälle zu unterscheiden:

(1) Der zufällige Wiederverkaufswert beträgt weniger als 65 GE, beispielsweise 51 GE
➔ Verlust für Sie in Höhe von 51 GE – 65 GE = -14 GE
(2) Der zufällige Wiederverkaufswert beträgt 65 GE
➔ Nullgewinn für Sie, da 65 GE – 65 GE = 0 GE
(3) Der zufällige Wiederverkaufswert beträgt mehr als 65 GE, beispielsweise 79 GE
➔ Gewinn für Sie in Höhe von 79 GE – 65 GE = 14 GE

Steigen Sie vorher aus der Auktion aus, so ist die Auktion für Sie beendet und Sie erzielen einen Nullgewinn.

2. Ablauf des Experiments

Im Anschluss an die Anleitungsphase findet zunächst eine Proberunde statt, in der eine Auktion zum besseren Verständnis der Teilnehmer probeweise durchgespielt wird. Die Gewinne und Verluste der Proberunde werden nicht verrechnet. Nach der Proberunde findet eine **5-minütige** Ruhephase statt, in der auf Ihrem Experimentsystem ein Fixierungskreuz angezeigt wird. Die Ruhephase ist für die Auswertung der physiologischen Daten zwingend erforderlich. Verhalten Sie sich während dieser Ruhephase ruhig, vermeiden Sie Bewegungen und entspannen Sie sich.

Der anschließende Hauptteil des Experiments besteht aus **15 Durchgängen**, in denen jeder der insgesamt 6 Teilnehmer des Experiments in eine Gruppe mit je zwei Computeragenten eingeteilt wird. In jedem Durchgang nehmen Sie und die beiden Computeragenten Ihrer Gruppe als Bieter an **einer** Auktion wie oben beschrieben teil. Die Computeragenten verfolgen einen Ihnen unbekannte Strategie. Nach jedem Durchgang werden Sie erneut zufällig zwei anderen Computeragenten zugeteilt. Sie werden also im Verlauf der 15 Durchgänge mit ständig wechselnden Computeragenten spielen. Die Ergebnisse einer Auktion haben keinerlei Auswirkungen auf die darauffolgenden Auktionen. Vor jedem Durchgang findet eine **1-minütige** Ruhephase statt.

3. Auszahlung

Zu Beginn des Experiments erhalten Sie eine Anfangsausstattung von **75 GE**, die Ihnen auf Ihrem Experimentkonto gutgeschrieben wird. Auf diesem Konto verrechnet die Experimentsoftware auch Ihre Gewinne und Verluste, die Sie während den insgesamt 15 Auktionen erwirtschaften. Ihr Kontoschlussstand wird Ihnen nach dem Experiment ***BAR*** ausbezahlt. 10 GE im Experiment entsprechen einer Auszahlung von 2 EUR.

4. ... und noch ein paar Bemerkungen zum Schluss

Sollten Sie Fragen zu dem Experiment haben, bleiben Sie bitte ruhig an Ihrem Platz sitzen und geben Sie dem Experimentleiter durch Handzeichen ein Signal. Warten Sie bitte, bis der Experimentleiter an Ihrem Platz ist, und stellen Sie dann Ihre Frage so leise wie möglich.

Verwenden Sie für die Interaktion mit Ihrem Experimentsystem ausschließlich Ihre freie Hand. Die mit der Messtechnik verbundene Hand muss während des gesamten Experiments ruhig gehalten werden. Vermeiden Sie möglichst jede Bewegung, da dies die Ergebnisse der Messungen verfälschen kann. Bleiben Sie auch nach Ende des Experiments an Ihrem Platz und warten Sie, bis die Experimentleitung die Messelektroden von Ihrer Haut entfernt hat. Die Teilnehmeranleitung sowie der Notizblock bleiben nach dem Experiment an Ihrem Platz zurück.

Bevor das Experiment beginnt, werden Ihnen an Ihrem Bildschirm zunächst einige Verständnisfragen zu den Regeln dieses Experiments gestellt. Geben Sie bitte die jeweiligen Antworten an Ihrem Computer ein. Im Anschluss daran findet eine Auktion wie oben beschrieben in einem

Probedurchlauf statt, in der Gewinne und Verluste nicht verrechnet werden. Danach startet die 5-minütige Ruhephase und damit das eigentliche Experiment.

Wichtiger Hinweis: Achten Sie bitte unbedingt darauf, dass Sie während des gesamten Experiments Ihre Maus so leise wie möglich bedienen und insbesondere beim Klicken nur sehr wenig Kraft einsetzen. Sie werden nun von der Experimentleitung einen Gehörschutz bekommen, um den Einfluss von Störgeräuschen auf die Messdaten zu reduzieren.

Bitte geben Sie hier Ihre Teilnehmer-Identifikation an:
____

Nachbefragung

Wie alt sind Sie?

_______ Jahre

Sind Sie

☐ männlich
☐ weiblich

Studieren Sie ein Fach mit wirtschaftswissenschaftlicher Ausrichtung?

☐ ja
☐ nein

Haben Sie schon einmal an Experimenten mit physiologischen Messungen teilgenommen?

☐ ja
☐ nein

Haben Sie bereits an Auktionsexperimenten teilgenommen?

☐ ja
☐ nein

Wie schätzen Sie Ihre Kenntnisse im Bereich Auktionen ein?

☐ Experte
☐ Grundkenntnisse
☐ Laie

[bitte wenden]

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

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

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

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

2. ____ Ich behalte meine Gefühle für mich.

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

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

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

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

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

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

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

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

Ich habe die vorhergehenden Fragen wahrheitsgemäß ausgefüllt?	JA / NEIN
Haben Sie bereits an Erstpreisauktionsexperimenten teilgenommen?	JA / NEIN

Vielen Dank für die Teilnahme

Teilnehmeranleitung

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

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

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

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

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

[bitte wenden]

Teilnehmer-Identifikation: ____________________

Entscheidungsblatt

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

Teilnehmer-Identifikation: ______________________

Fragebogen

Bitte lesen Sie diese Hinweise zunächst sorgfältig durch. Auf den folgenden Seiten finden Sie insgesamt **20 Aussagen**, die sich zur Beschreibung ihrer Eindrücke aus dem Experiment eignen. Kreuzen Sie bitte an:

SA (starke Ablehnung), wenn Sie der Aussage auf keine Fall zustimmen oder sie für völlig unzutreffend halten	~~SA~~ | A | N | Z | SZ
A (Ablehnung), wenn Sie der Aussage eher nicht zustimmen oder sie für unzutreffend halten	SA | ~~A~~ | N | Z | SZ
N (neutral), wenn die Aussage weder richtig noch falsch, also weder zutreffend noch unzutreffend ist	SA | A | ~~N~~ | Z | SZ
Z (Zustimmung), wenn Sie der Aussage eher zustimmen oder sie für zutreffend halten	SA | A | N | ~~Z~~ | SZ
SZ (starke Zustimmung), wenn Sie der Aussage nachdrücklich zustimmen oder sie für völlig zutreffend halten.	SA | A | N | Z | ~~SZ~~

Ihre Antworten werden **absolut anonym** erhoben und verarbeitet. Eine Zuordnung zwischen Ihnen und den Antworten ist daher nicht möglich. Im Anschluss daran teilen Sie uns bitte Anmerkungen und Kommentare zu diesem Experiment, sowie stichpunktartig Ihre Strategie mit, nach der Sie vorgegangen sind.

Blättern Sie nun bitte um, und beginnen Sie mit der Beantwortung.

SA = Starke Ablehnung **A = Ablehnung** **N = Neutral** **Z = Zustimmung** **SZ = Starke Zustimmung**

Seite **1** von **3**

1.	Ich habe mir vor jeder Auktion einen klaren Preis gesetzt, bei dem ich aus der Auktion aussteigen wollte.	SA / A / N / Z / SZ
2.	Der Auktionsmechanismus, der in diesem Experiment verwendet wurde, ist spannend.	SA / A / N / Z / SZ
3.	Ich habe es einem anderen Teilnehmer nicht gegönnt, wenn er in einer Auktion einen Gewinn erzielte.	SA / A / N / Z / SZ
4.	Ich bin nie zum einem niedrigeren Preis ausgestiegen als ich ursprünglich vorhatte.	SA / A / N / Z / SZ
5.	Ich stand in starker Konkurrenz zu den anderen Teilnehmern des Experiments.	SA / A / N / Z / SZ
6.	Ich habe mich darüber geärgert, wenn ein anderer Bieter lange an der Auktion teilgenommen hat.	SA / A / N / Z / SZ
7.	Ich habe in Auktionen teilweise länger mit dem Aussteigen gewartet als ich ursprünglich vorhatte.	SA / A / N / Z / SZ
8.	Ich war während der Teilnahme an den Auktionen aufgeregt.	SA / A / N / Z / SZ
9.	Das Gewinnen einer Auktion an sich war für mich wichtiger als die Höhe meiner Auszahlung.	SA / A / N / Z / SZ
10.	Die Auszahlungen der anderen Teilnehmer haben in meinen Entscheidungen eine große Rolle gespielt.	SA / A / N / Z / SZ
11.	Ich habe mir vor einer Auktion keine Gedanken gemacht, bis zu welchem Preis ich bieten wollte.	SA / A / N / Z / SZ
12.	Der in diesem Experiment verwendete Auktionsmechanismus ist langweilig.	SA / A / N / Z / SZ
13.	Ich war eher bereit länger an der Auktion teilzunehmen, als dass ein anderer Teilnehmer einen Gewinn erzielt hätte.	SA / A / N / Z / SZ
14.	Ich bin in Auktionen teilweise zu einem niedrigeren Preis ausgestiegen als ich ursprünglich vorhatte.	SA / A / N / Z / SZ
15.	Die anderen Teilnehmer des Experiments befanden sich nicht in einem Wettbewerb mit mir.	SA / A / N / Z / SZ
16.	Es hat mir nichts ausgemacht, wenn ich aus der Auktion ausgestiegen bin und damit ein anderer Teilnehmer die Auktion gewonnen hat.	SA / A / N / Z / SZ
17.	Ich bin nie erst zu einem höheren Preis ausgestiegen als ich ursprünglich vorhatte.	SA / A / N / Z / SZ
18.	Ich war während der Teilnahme an Auktionen nicht aufgeregt.	SA / A / N / Z / SZ
19.	Die Höhe meiner Auszahlung war für mich entscheidend – das Gewinnen an sich war für mich nebensächlich.	SA / A / N / Z / SZ
20.	Die Auszahlungen der anderen Teilnehmer waren für mich unwichtig.	SA / A / N / Z / SZ

Wie haben Sie festgelegt bei welchem Preis Sie aussteigen? Falls Sie ein Preislimit hatten, welches?

SA = Starke Ablehnung **A = Ablehnung** **N = Neutral** **Z = Zustimmung** **SZ = Starke Zustimmung**

Seite **2** von **3**

Kommentare und Anmerkungen

-Abgabe freiwillig-

…zu Ihrer Strategie:

…zu diesem Experiment:

SA = Starke Ablehnung **A = Ablehnung** **N = Neutral** **Z = Zustimmung** **SZ = Starke Zustimmung**

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Appendix B.

Supplementary Material for Chapter 3

Participant Instructions and Questionnaires of Laboratory

This section list examples of instruction- and questionnaire documents that are used in the study of Chapter 3. There are the following documents listed: exemplary instruction for the “High time pressure” treatment and the psychometric scales used to assess competitive arousal. The risk aversion questionnaire is identical to the one used in the study of Chapter 2, which is listed in Appendix A.

Teilnehmeranleitung

Sie nehmen an einem Experiment teil, bei dem Entscheidungsverhalten untersucht wird. Während des Experiments wird Ihr Hautleitwert, Herzrate und Puls aufgezeichnet und in der späteren Analyse mit ausgewertet. Sie können bei diesem Experiment ***echtes Geld*** verdienen. Wie viel Sie verdienen, hängt sowohl von Ihren Entscheidungen als auch von den Entscheidungen der anderen Teilnehmer ab. Kommunikation zwischen den Teilnehmern ist nicht erlaubt. Der Hauptteil des Experiments besteht aus einer Folge von 4 Auktionen. Am Ende des Experiments erhalten Sie **15 Euro** zuzüglich der von Ihnen erwirtschafteten Gewinne und abzüglich der von Ihnen verursachten Verluste. In diesem Experiment wird in Geldeinheiten (GE) gerechnet. 10 GE entsprechen einem realen Geldbetrag von 2 EUR.

1. Aufbau und Ablauf einer Auktion

Bei jeder Auktion bieten Sie und zwei weitere Teilnehmer auf ein fiktives Gut, welches zum Verkauf steht. Bei der Auktion wird ausgehend von einem Startwert von 90 GE der aktuelle Preis rundenweise um 5 GE erhöht. In jeder Runde haben Sie über die Schaltfläche „Bieten" die Möglichkeit, ein Gebot in Höhe des aktuellen Preises abzugeben. Falls Sie auf „Aussteigen" klicken, so geben Sie in dieser Runde kein Gebot ab und steigen aus der Auktion aus. Eine Runde dauert genau 5 Sekunden. Diese Zeit wird Ihnen durch einen Countdown dargestellt. Sollten Sie die Zeit verstreichen lassen ohne ein Gebot abzugeben, so ist dies gleichbedeutend mit „Aussteigen".

Eine Auktion endet, wenn entweder (i) nur noch genau einer der drei Bieter ein Gebot in Höhe des aktuellen Preises abgibt oder (ii) keiner der drei Bieter ein Gebot in Höhe des aktuellen Preises abgibt. Es gibt also insgesamt 3 Fälle zu unterscheiden:

(1) Eine Auktion endet, weil nur noch genau <u>**einer**</u> der drei Bieter ein Gebot in Höhe des aktuellen Preises abgegeben hat. Dieser Bieter erwirbt das Gut für den dann gültigen Preis.

(2) Eine Auktion endet oberhalb des Startpreises, weil <u>**keiner**</u> der drei Bieter ein Gebot in Höhe des aktuellen Preises abgegeben hat. In diesem Fall wird zufällig einer der Bieter als Gewinner der Auktion ausgelost, der in der vorherigen Runde ein Gebot abgegeben hat. Dieser Bieter erwirbt das Gut für den Preis der vorherigen Runde (Aktueller Preis – 5 GE).

(3) Sollte bereits beim Startpreis <u>**keiner**</u> der drei Bieter bereit sein, ein Gebot abzugeben, so endet die Auktion und keiner der Bieter erwirbt das Gut.

Sofern Sie der Gewinner sind, so berechnet sich Ihr Ertrag dieser Auktion nach folgender Formel:

Ertrag = Wiederverkaufswert - Kaufpreis

Der Wiederverkaufswert des Gutes ist für alle Bieter **identisch**, ist jedoch vor und während der Auktion nicht bekannt. Der Wiederverkaufswert wird zufällig aus den Zahlen zwischen **110** und **155** gezogen nachdem die Auktion beendet wurde. Jede Zahl zwischen 110 und 155 hat dabei die **gleiche Wahrscheinlichkeit** gezogen zu werden. Das ist so, als ob 46 Kugeln, die jeweils mit einer Zahl zwischen 110 und 155 beschriftet sind, in einer Urne abgelegt werden. Ein Zufallszug aus der Urne bestimmt dann den Wiederverkaufswert des Gutes dieser Auktion.

Der Gewinner der Auktion erhält den Wert des Gutes abzüglich seines Gebotes. Dieser Zusammenhang soll an einem Beispiel verdeutlicht werden. Nehmen wir an, Sie haben die Auktion mit einem Preis von 125 GE gewonnen. Nun gibt es folgende Fälle zu unterscheiden:

(1) Der zufällige Wiederverkaufswert beträgt weniger als 125 GE, beispielsweise 114 GE
➔ Verlust für Sie in Höhe von 114 GE – 125 GE = -11 GE

(2) Der zufällige Wiederverkaufswert beträgt 125 GE
➔ Nullgewinn für Sie, da 125 GE – 125 GE = 0 GE

(3) Der zufällige Wiederverkaufswert beträgt mehr als 125 GE, beispielsweise 134 GE
➔ Gewinn für Sie in Höhe von 136 GE – 125 GE = 11 GE

Falls Sie nicht der Gewinner der Auktion sind, so erzielen Sie einen Nullgewinn.

2. Ablauf des Experiments

Im Anschluss an die Anleitungsphase findet zunächst eine **5-minütige** Ruhephase statt, in der auf Ihrem Experimentsystem ein Fixierungskreuz angezeigt wird. Die Ruhephase ist für die Auswertung der physiologischen Daten zwingend erforderlich. Verhalten Sie sich während dieser Ruhephase ruhig, vermeiden Sie Bewegungen und entspannen Sie sich. Danach findet eine Probeauktion statt, in der eine Auktion zum besseren Verständnis der Teilnehmer probeweise durchgespielt wird. Die Gewinne und Verluste der Probeauktion werden nicht verrechnet. In der Probeauktion werden die Gebote der anderen Bieter durch Computeragenten simuliert. Bei der Probeauktion interagieren Sie also **<u>nicht</u>** mit den anderen Teilnehmern.

Der anschließende Hauptteil des Experiments besteht aus **4 Durchgängen**, in denen die insgesamt 9 Teilnehmer des Experiments jeweils erneut zufällig auf drei Dreiergruppen aufgeteilt werden. In jedem Durchgang nehmen Sie und die beiden anderen Teilnehmer Ihrer Gruppe als Bieter an **einer** Auktion wie oben beschrieben teil. Nach jedem Durchgang werden Sie erneut zufällig mit zwei anderen Bietern einer Dreiergruppe zugeteilt. Sie werden also im Verlauf der 4 Durchgänge mit ständig wechselnden Bietern spielen. Dabei ist sichergestellt, dass Sie mit keinem der anderen Teilnehmer mehr als einmal an einer Auktion teilnehmen. Die Ergebnisse einer Auktion haben keinerlei Auswirkungen auf die darauffolgenden Auktionen. Vor jedem Durchgang findet erneut eine **4-minütige** Ruhephase statt.

3. Auszahlung

Zu Beginn des Experiments erhalten Sie eine Anfangsausstattung von **75 GE**, die Ihnen auf Ihrem Experimentkonto gutgeschrieben wird. Auf diesem Konto verrechnet die Experimentsoftware auch Ihre Gewinne und Verluste, die Sie während den insgesamt 4 Auktionen erwirtschaften. Ihr Kontoschlussstand wird Ihnen nach dem Experiment ***bar*** ausgezahlt. 10 GE im Experiment entsprechen einer Auszahlung von 2 EUR.

4. ... und noch ein paar Bemerkungen zum Schluss

Sollten Sie Fragen zu dem Experiment haben, bleiben Sie bitte ruhig an Ihrem Platz sitzen und geben Sie dem Experimentleiter durch Handzeichen ein Signal. Warten Sie bitte, bis der Experimentleiter an Ihrem Platz ist, und stellen Sie dann Ihre Frage so leise wie möglich.

Verwenden Sie für die Interaktion mit Ihrem Experimentsystem ausschließlich Ihre freie Hand. Die mit der Messtechnik verbundene Hand muss während des gesamten Experiments ruhig gehalten werden. Vermeiden Sie möglichst jede Bewegung, da dies die Ergebnisse der Messungen verfälschen kann. Bleiben Sie auch nach Ende des Experiments an Ihrem Platz und warten Sie, bis die Experimentleitung die Messelektroden von Ihrer Haut entfernt hat. Die Teilnehmeranleitung sowie der Notizblock bleiben nach dem Experiment an Ihrem Platz zurück.

Bevor das Experiment beginnt, werden Ihnen an Ihrem Bildschirm zunächst einige Verständnisfragen zu den Regeln dieses Experiments gestellt. Geben Sie bitte die jeweiligen Antworten an Ihrem Computer ein. Im Anschluss daran startet die 5-minütige Ruhephase. Danach findet eine Auktion wie oben beschrieben in einem Probedurchlauf statt, in der Gewinne und Verluste nicht verrechnet werden. Danach beginnt das eigentliche Experiment.

Wichtiger Hinweis: Achten Sie bitte unbedingt darauf, dass Sie während des gesamten Experiments Ihre Maus so leise wie möglich bedienen und insbesondere beim Klicken nur sehr wenig Kraft einsetzen. Sie werden nun von der Experimentleitung einen Gehörschutz bekommen, um den Einfluss von Störgeräuschen auf die Messdaten zu reduzieren.

Nachbefragung

Bitte geben Sie hier Ihre Teilnehmer-Identifikation an:
____

Wie alt sind Sie?

_______ Jahre

Sind Sie

☐ männlich
☐ weiblich

Studieren Sie ein Fach mit wirtschaftswissenschaftlicher Ausrichtung?

☐ ja
☐ nein

Wie oft haben Sie vorher schon an Auktionsexperimenten teilgenommen?

_______ Mal

Gefühle während der Auktionen

Wir möchten Ihnen gerne einige Fragen zu Ihren Gefühlen stellen, die Sie während der Teilnahme an den eben durchgeführten Auktionen empfanden. Bitte beantworten Sie die Fragen, indem Sie folgende Antwortmöglichkeiten benutzen (ein Kreuz pro Zeile).

Gefühl	Antwort										
	Überhaupt nicht					Neutral					Sehr stark
1.) Aktiv/Rege *(Active)*	1	2	3	4	5	6	7	8	9	10	11
2.) Erregt/Aufgeregt *(Aroused)*	1	2	3	4	5	6	7	8	9	10	11
3.) Nervös *(Nervous)*	1	2	3	4	5	6	7	8	9	10	11
4.) Besorgt (Anxious)	1	2	3	4	5	6	7	8	9	10	11
5.) Unglücklich *(Unhappy)*	1	2	3	4	5	6	7	8	9	10	11
6.) Ängstlich *(Fearful)*	1	2	3	4	5	6	7	8	9	10	11
7.) Erregt/Begeistert *(Excited)*	1	2	3	4	5	6	7	8	9	10	11
8.) Gelassen *(Calm)*	1	2	3	4	5	6	7	8	9	10	11
9.) Zufrieden/Befriedigt *(Satisfied)*	1	2	3	4	5	6	7	8	9	10	11
10.) Freudig erregt/Beschwingt *(Elated)*	1	2	3	4	5	6	7	8	9	10	11
11.) Zufrieden/Erfreut *(Pleased)*	1	2	3	4	5	6	7	8	9	10	11
12.) Glücklich *(Happy)*	1	2	3	4	5	6	7	8	9	10	11
	Überhaupt nicht					Neutral					Sehr stark

[bitte wenden]

Nachbefragung

Motive und Eindrücke während der Auktionen

Bitte versetzen Sie sich erneut in die Situation während der Teilnahme an einer Auktion und geben Sie an, wie stark sie den folgenden Aussagen zustimmen oder sie ablehnen (ein Kreuz pro Zeile).

Aussage	Antwort										
	Starke Ablehnung					Neutral					Starke Zustimmung
1.) Ich war während der Auktion aufgeregt.	1	2	3	4	5	6	7	8	9	10	11
2.) Ich wollte die Auktion unbedingt gewinnen.	1	2	3	4	5	6	7	8	9	10	11
3.) Ich wollte die Auktion auf keinen Fall verlieren.	1	2	3	4	5	6	7	8	9	10	11
4.) Ich war während der Auktion gestresst.	1	2	3	4	5	6	7	8	9	10	11
5.) Wenn ich eine Auktion gewonnen habe, dann habe ich mich gefreut.	1	2	3	4	5	6	7	8	9	10	11
6.) Wenn ich eine Auktion verloren habe, dann war ich enttäuscht.	1	2	3	4	5	6	7	8	9	10	11
7.) Ich habe die anderen Bieter als "Gegner" wahrgenommen.	1	2	3	4	5	6	7	8	9	10	11
8.) Es hat mir Spaß gemacht, gegen die anderen Bieter zu bieten.	1	2	3	4	5	6	7	8	9	10	11
9.) Es war mir wichtig, die Auktion zu gewinnen.	1	2	3	4	5	6	7	8	9	10	11
10.) Es war mir wichtig, die Auktion nicht zu verlieren.	1	2	3	4	5	6	7	8	9	10	11
11.) Ich wollte für das Gut nicht zu viel bezahlen.	1	2	3	4	5	6	7	8	9	10	11
12.) Ich empfand während der Auktion ein Wettbewerbsgefühl.	1	2	3	4	5	6	7	8	9	10	11
13.) Ich habe manchmal irrational geboten.	1	2	3	4	5	6	7	8	9	10	11
14.) Es war mir wichtig, gegen die anderen Bieter zu gewinnen.	1	2	3	4	5	6	7	8	9	10	11
15.) Es war mir wichtig, gegen die anderen Bieter nicht zu verlieren.	1	2	3	4	5	6	7	8	9	10	11
16.) Ich habe manchmal meine Gebote im Nachhinein bereut.	1	2	3	4	5	6	7	8	9	10	11
17.) Ich habe mir während einer Auktion vorgestellt, wie schön es wäre, die Auktion zu gewinnen.	1	2	3	4	5	6	7	8	9	10	11
18.) Ich habe mir während einer Auktion vorgestellt, wie enttäuschend es wäre, die Auktion zu verlieren.	1	2	3	4	5	6	7	8	9	10	11
19.) Die Auktionen liefen so schnell, dass ich nicht in der Lage war, rechtzeitig zu bieten.	1	2	3	4	5	6	7	8	9	10	11
20.) Ich habe am Ende der Auktion manchmal mehr geboten, als ich ursprünglich vorhatte.	1	2	3	4	5	6	7	8	9	10	11
	Starke Ablehnung					Neutral					Starke Zustimmung

Nachbefragung

Bitte schätzen Sie im Folgenden Ihre Beanspruchung während der Teilnahme an den Auktionen ein (ein Kreuz pro Zeile).

Geistige Anforderung

1	2	3	4	5	6	7	8	9	10	11

Gering — Hoch

Wie viel geistige Anforderung war bei der Informationsaufnahme und bei der Informationsverarbeitung erforderlich (z.B. Denken, Entscheiden, Rechnen, Erinnern, Hinsehen, Suchen ...)? War die Aufgabe leicht oder anspruchsvoll, einfach oder komplex, erfordert sie hohe Genauigkeit oder ist sie fehlertolerant?

Zeitliche Anforderung

1	2	3	4	5	6	7	8	9	10	11

Gering — Hoch

Wie viel Zeitdruck empfanden Sie hinsichtlich der Häufigkeit oder dem Takt mit dem die Aufgaben oder Aufgabenelemente auftraten? War die Aufgabe langsam und geruhsam oder schnell und hektisch?

Leistung

1	2	3	4	5	6	7	8	9	10	11

Gut — Schlecht

Wie erfolgreich haben Sie Ihrer Meinung nach die vom Versuchsleiter (oder Ihnen selbst) gesetzten Ziele erreicht? Wie zufrieden waren Sie mit Ihrer Leistung bei der Verfolgung dieser Ziele?

Anstrengung

1	2	3	4	5	6	7	8	9	10	11

Gering — Hoch

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

Frustration

1	2	3	4	5	6	7	8	9	10	11

Gering — Hoch

Wie unsicher, entmutigt, irritiert, gestresst und verärgert (versus sicher, bestätigt, zufrieden, entspannt und zufrieden mit sich selbst) fühlten Sie sich während der Aufgabe?

Bitte vergleichen Sie im Folgenden die einzelnen Dimensionen Ihrer Beanspruchung und geben Sie **für jedes Paar** an, welche Dimension Sie jeweils als intensiver empfunden haben (ein Kreuz pro Zeile).

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

Nachbefragung

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

Frage	**Antwort**										
	Stimmt überhaupt nicht					Neutral					Stimmt vollkommen
1.) Wenn ich *mehr positive* Gefühle (wie Freude oder Heiterkeit) empfinden möchte, ändere ich, woran ich denke.	1	2	3	4	5	6	7	8	9	10	11
2.) Ich behalte meine Gefühle für mich.	1	2	3	4	5	6	7	8	9	10	11
3.) Wenn ich *weniger negative* Gefühle (wie Traurigkeit oder Ärger) empfinden möchte, ändere ich, woran ich denke.	1	2	3	4	5	6	7	8	9	10	11
4.) Wenn ich *positive* Gefühle empfinde, bemühe ich mich, sie *nicht* nach außen zu zeigen.	1	2	3	4	5	6	7	8	9	10	11
5.) Wenn ich in eine stressige Situation gerate, ändere ich meine Gedanken über die Situation so, dass es mich beruhigt.	1	2	3	4	5	6	7	8	9	10	11
6.) Ich halte meine Gefühle unter Kontrolle, indem ich sie *nicht* nach außen zeige.	1	2	3	4	5	6	7	8	9	10	11
7.) Wenn ich *mehr positive* Gefühle empfinden möchte, versuche ich über die Situation anders zu denken.	1	2	3	4	5	6	7	8	9	10	11
8.) Ich halte meine Gefühle unter Kontrolle, indem ich über meine aktuelle Situation anders nachdenke.	1	2	3	4	5	6	7	8	9	10	11
9.) Wenn ich *negative* Gefühle empfinde, sorge ich dafür, sie *nicht* nach außen zu zeigen.	1	2	3	4	5	6	7	8	9	10	11
10.) Wenn ich *weniger negative* Gefühle empfinden möchte, versuche ich über die Situation anders zu denken.	1	2	3	4	5	6	7	8	9	10	11
	Stimmt überhaupt nicht					Neutral					Stimmt vollkommen

Ich habe die vorhergehenden Fragen wahrheitsgemäß ausgefüllt? JA / NEIN

Vielen Dank für die Teilnahme

Avatar Names and Images

List of all used avatar names and images used in the laboratory experiment in Chapter 3. Each participant was shown one variation of names and images from which they could chose.

Table B.1.: Overview of all avatar names used in the experiment in Chapter 3.

Variation 1: bullet_bidder, bullet_hero, bullet_champion, star_bidder, star_hero, star_champion, target_bidder, target_hero, target_champion
Variation 2: auction_hammer, victory_hammer, battle_hammer, auction_flash, victory_flash, battle_flash, auction_punch, victory_punch, battle_punch
Variation 3: sword_pirate, sword_sniper, sword_striker, thunder_pirate, thunder_sniper, thunder_striker, turbo_pirate, turbo_sniper, turbo_striker
Variation 4: bidding_granade, combat_granade, shopping_granade, bidding_monster, combat_monster, shopping_monster, bidding_rocket, combat_rocket, shopping_rocket
Variation 5: fire_knight, fire_eagle, fire_tiger, fortress_knight, fortress_eagle, fortress_tiger, axe_knight, axe_eagle, axe_tiger
Variation 6: bomb_warrior, bomb_racer, bomb_maniac, nuclear_warrior, nuclear_racer, nuclear_maniac, crazy_warrior, crazy_racer, crazy_maniac
Variation 7: devil_fighter, devil_monkey, devil_vampire, claw_fighter, claw_monkey, claw_vampire, dynamite_fighter, dynamite_monkey, dynamite_vampire
Variation 8: toxic_hunter, toxic_boss, toxic_snake, cannon_hunter, cannon_boss, cannon_snake, ninja_hunter, ninja_boss, ninja_snake
Variation 9: energy_trooper, energy_winner, energy_joker, tornado_trooper, tornado_winner, tornado_joker, shark_trooper, shark_winner, shark_joker

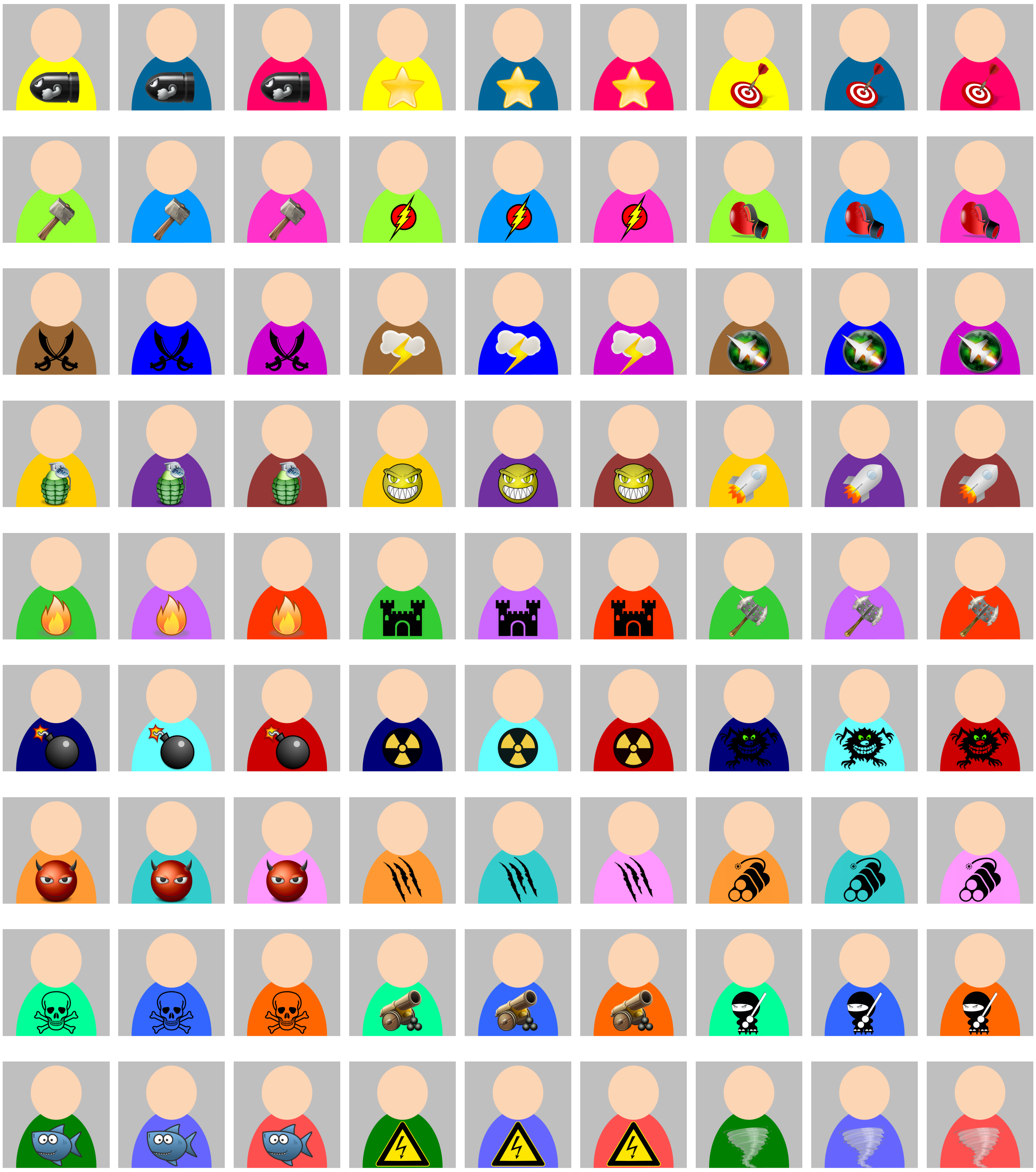

Figure B.1.: Overview of all avatar images used in the experiment in Chapter 3. Each line of images represents one variation (variation one to nine) shown to a participant.

Appendix C.

Supplementary Material for Chapter 5

Complete Overview of searched IS outlets

The following tables show the complete list of publication outlets that were used in literature research as described in Chapter 5.

Table C.1.: Overview of searched A*-ranked IS Journals.

	bio		physio		neuro		
Name	**f**	**r**	**f**	**r**	**f**	**r**	**comment**
ACM Transactions on Computer-Human Interaction	1	1	7	3	0	0	
Decision Support Systems	0	0	0	0	0	0	
European Journal of Information Systems	0	0	0	0	0	0	title only
Information and Management	0	0	0	0	0	0	
Information and Organization	0	0	0	0	0	0	
Information Systems Journal	0	0	0	0	0	0	
Information Systems Research	0	0	0	0	0	0	title & keywords
Journal of Information Technology	1	0	0	0	1	0	title only
Journal of Management Information Systems	1	1	0	0	2	1	keywords only
Journal of Strategic Information Systems	0	0	0	0	0	0	
Journal of the Association for Information Science and Technology	0	0	1	0	0	0	
Journal of the Association for Information Systems	0	0	0	0	0	0	
Management Information Systems Quarterly	0	0	0	0	0	0	

Abbreviations: f = found, r = relevant

Table C.2.: Overview of searched A-ranked IS Journals.

	bio		physio		neuro		
Name	**f**	**r**	**f**	**r**	**f**	**r**	**comment**
Applied Ontology	0	0	0	0	0	0	
Australasian Journal of Information Systems	0	0	1	0	0	0	
Behaviour and Information Technology	0	0	0	0	0	0	
British Journal of Educational Technology	0	0	5	0	0	0	
Business & Information Systems Engineering	0	0	0	0	0	0	
Communications of the ACM	0	0	0	0	0	0	
Communications of the Association for Information Systems	0	0	0	0	0	0	
Computers and Security	0	0	0	0	0	0	
Data and Knowledge Engineering	0	0	1	0	0	0	
DATA BASE for Advances in Information Systems	0	0	0	0	0	0	
Electronic Commerce Research	0	0	0	0	0	0	
Electronic Markets - The International Journal on Networked Business	0	0	0	0	0	0	
Enterprise Information Systems	0	0	0	0	0	0	
Group Decision and Negotiation	0	0	0	0	0	0	
Human-Computer Interaction	0	0	7	0	1	0	
IBM Systems Journal	0	0	0	0	0	0	
Information and Software Technology	0	0	1	0	0	0	
Information Communication and Society	0	0	0	0	0	0	
Information Systems	0	0	0	0	0	0	
Information Systems Frontiers	0	0	0	0	0	0	
Information Technology and People	1	0	0	0	0	0	
International Journal of Cooperative Information Systems	0	0	0	0	0	0	
International Journal of Electronic Commerce	0	0	0	0	0	0	
International Journal of Information Management	0	0	1	0	0	0	
International Journal of Medical Informatics	7	1	23	0	1	0	
Internet Research	0	0	0	0	0	0	
Journal of Computer Information Systems	0	0	0	0	0	0	
Journal of Global Information Management	0	0	0	0	0	0	
Journal of Information Systems	0	0	0	0	0	0	
Journal of Information Technology Theory and Application	0	0	0	0	0	0	
Journal of Knowledge Management	0	0	0	0	0	0	
Journal of Organizational Computing and Electronic Commerce	0	0	0	0	0	0	
Journal of the American Medical Informatics Association	0	0	3	0	0	0	
Knowledge Management Research and Practice	0	0	0	0	0	0	title only
Knowledge-Based Systems	1	0	0	0	1	0	
MISQ Executive	0	0	1	0	0	0	
New Technology, Work and Employment	0	0	0	0	0	0	
Personal and Ubiquitous Computing	9	2	0	0	1	1	
Scandinavian Journal of Information Systems	0	0	0	0	0	0	
The Information Society	0	0	0	0	0	0	

Abbreviations: f = found, r = relevant

Table C.3.: Overview of searched IS Conferences.

Name	bio f	bio r	physio f	physio r	neuro f	neuro r	comment
International Conference on Information Systems	0	0	2	0	0	0	
Americas Conference on Information Systems	0	0	3	0	0	0	
European Conference on Information Systems	2	2	3	1	1	1	
Pacific Asia Conference on Information Systems	0	0	0	0	0	0	
International Conference on Information Systems Development	0	0	0	0	0	0	
International Conference on Mobile Business	0	0	0	0	0	0	
Mediterranean Conference on Information Systems	0	0	1	0	0	0	
Wuhan International Conference on e-Business	0	0	0	0	0	0	
Australasian Conference on Information Systems	0	0	0	0	0	0	
International Conference on Information Resources Management	0	0	1	0	0	0	

Abbreviations: f = found, r = relevant

Table C.4.: Overview of searched HCI and related IS Outlets.

Name	bio f	bio r	physio f	physio r	neuro f	neuro r	comment
HIC International Conference	4	2	2	1	1	0	
International Conference on Engineering Psychology and Cognitive Ergonomics							
International Conference on Universal Access in Human-Computer Interaction							
International Conference on Virtual, Augmented and Mixed Reality							
International Conference on Cross-Cultural Design							
International Conference on Social Computing and Social Media							
International Conference on Augmented Cognition							
International Conference on Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management							
International Conference on Design, User Experience and Usability							
International Conference on Distributed, Ambient and Pervasive Interactions							
International Conference on Human Aspects of Information Security, Privacy and Trust							
International Conference on HCI in Business, Government and Organizations							
International Conference on Learning and Collaboration Technologies							
International Conference on Human Aspects of IT for the Aged Population							
Special Interest Group on Human-Computer Interaction	63	19	0	0	7	3	

Abbreviations: f = found, r = relevant

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List of Abbreviations

AAPB	Association for Applied Psychophysiology and Biofeedback
AIS	Association for Information Systems
ANN	Artificial Neural Network
ANS	Autonomic Nervous System
BCIA	Biofeedback Certification International Alliance
bpm	Beats Per Minutes
CAR	Competitive Arousal
CF	Candidate Features
DTW	Desire to Win
EA	Evolutionary Algorithm
ECG	Electrocardiography
EDA	Electrodermal Activity
EEG	Electroencephalography
fLBF	Foreign Live-Biofeedback
fMRI	Functional Magnetic Resonance Imaging
fNIRS	Functional Near-Infrared Spectroscopy
FOL	Fear of Losing
FPSB	First-Price Sealed-Bid
HCI	Human-Computer Interaction
HR	Heart Rate
HRV	Heart Rate Variability
HTP	High Time Pressure
IBI	Inter-Beat-Interval
ICD	Initial Cool Down
IS	Information System
ISC	Increased Social Competition
ISNR	International Society for Neurofeedback and Research
KIT	Karlsruhe Institute of Technology
LBF	Live-Biofeedback
LTP	Low Time Pressure

min	Minute
MLR	Multiple Linear Regression
ms	Milliseconds
MTP	Medium Time Pressure
MU	Monetary Unit
NASA TLX	NASA Task Load Index
NIRS	Near-Infrared Spectroscopy
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
NTP	No Time Pressure
RP	Rest Period
SC	Skin Conductance
SCL	Skin Conductance Level
SCO	Social Competition
SCR	Skin Conductance Response
SCR.amp	Skin Conductance Response Amplitude
sec	Second

List of Figures

List of Symbols

δ	Price increment
€	Euro
τ	Time increment
θ	Normalization
t_s	Auction start
t_r	Start resale value range
t_v	Expected value
t_e	Auction end
a	Auction observation
$f(a)$	Prediction of auction observation
a	Mean of a
S	Feature subset size
x	Individual of EA
y	Regression dependent variable
α	Regression intercept
β	Regression coefficient
ϵ	Regression residuals

List of Tables