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Research Article

The Impact of Computerized Agents on Immediate Emotions, Overall Arousal and Bidding Behavior in Electronic Auctions

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Abstract

The presence of computerized agents has become pervasive in everyday live. In this paper, we examine the impact of agency on human bidders' affective processes and bidding behavior in an electronic auction environment. In particular, we use skin conductance response and heart rate measurements as proxies for the immediate emotions and overall arousal of human bidders in a lab experiment with human and computerized counterparts. Our results show that computerized agents mitigated 1) the intensity of bidders' immediate emotions in response to discrete auction events, such as submitting a bid and winning or losing an auction, and 2) the bidders' overall arousal levels during the auction. Moreover, agency affected bidding behavior and its relation to overall arousal: whereas overall arousal and bids were negatively correlated when competing against human bidders, we did not observe this relationship for computerized agents. In other words, lower levels of agency yield less emotional behavior. The results of our study have implications for the design of electronic auction platforms and markets that include both human and computerized actors.

Keywords: *Agency, Auctions, E-Commerce, NeuroIS, Emotions, Arousal, Human-Computer Interaction.*

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The Impact of Computerized Agents on Immediate Emotions, Overall Arousal and Bidding Behavior in Electronic Auctions

1. Introduction

Information technology has revolutionized markets. While a market was traditionally a place where people came together to trade, a large portion of today's trading activity in markets is actually conducted by and with computerized trading agents. A necessary precursor to this development is the ubiquitous adoption of electronic markets in industry and government (Bakos, 1991). Today, electronic markets are pervasive and an integral part of our everyday life. Billions of transactions take place in electronic markets and platforms on a daily basis. They may be as small as the purchase of an electronic newspaper or as large as in financial and spectrum auctions. In particular, auctions are frequently used in electronic consumer markets (e.g., ebay.com, dubli.com, madbid.com). Regardless of market size, bidding, searching, matching, clearing, and settlement processes are all supported by IT systems designed to reduce transaction costs, increase the probability of finding trading partners, and support complex decision making. For the most part, society has come to accept the fact that humans are no longer actively performing many of these tasks. As markets have automated and increased their operating speeds, so have the participants in these markets. They rely on computerized agents to represent their interests, such as sniping agents on eBay employed “to avoid a bidding war” (Ariely, Ockenfels, & Roth, 2005, p. 896).

In contemporary financial markets, one has a greater chance to trade with an algorithm than with a human being (Brogaard, Hendershott, & Riordan, 2014). Demonstrating the importance of computerized traders, Hendershott and colleagues show that algorithmic traders were responsible for a large increase in liquidity available on the New York Stock Exchange (Hendershott, Jones, & Menkveld, 2011). Taken as a whole, computerized traders presumably are responsible for over 70 percent of the volume in U.S. stock markets (Brownlees, Cipollini, & Gallo, 2011). A subset of computerized traders called high-frequency traders (HFT) make up more than 40 percent of the trading volume on Nasdaq and have been shown to be more informed than non-HFTs (Brogaard et al., 2014). Clearly, computerized traders play an important role in electronic markets today. As part of this development, they also became *competitors* of human traders. The research on the impact of computerized traders on human traders' affective processes and behavior and on overall market efficiency is still in its infancy, and it is unclear how accepting market participants are of this trend. However, given the amount of negative public press surrounding algorithmic and high-frequency trading in financial markets, we can safely assume that some participants are unhappy about the situation (Strasbourg & Patterson, 2012). As such, we might ask how the increasing importance of computerized agents in electronic auctions and the degree to which users' believe they are interacting with human or non-human actors (agency) influences their decision making processes.

To study the impact of agency on market participants' behavior, affective processes, and market efficiency, we conducted a neuroIS laboratory experiment in which participants bidded against other human participants in one treatment (high agency) and against computerized bidding agents in the other treatment (low agency). The level of agency was the only meaningful difference between treatments. Applying neuroIS methods was particularly insightful in this study because they allowed us to measure proxies for market participants' affective processes that may partially be unconscious in nature. Moreover, neuroIS enabled us to assess this data at different stages of the auction process without having to interrupt the participants during decision making (Riedl, Davis, & Hevener, 2014a; vom Brocke & Liang, 2014). In particular, we measured participants' heart rates (HR) and skin conductance responses (SCR) as proxies for their overall arousal and their immediate emotions. We combine these measures with market results to provide insights into participants' affective processes during auctions and in response to discrete auction events, such as submitting a bid and winning or losing an auction. By capturing participants' overall arousal and immediate emotions in different scenarios (human opponents/computer opponents; that is, high agency and low agency), we explore recent developments in electronic markets and take a step towards explaining the impact of emotions.

Our results show that participants were significantly more aroused in the high-agency treatment (human opponents) than in the low-agency treatment (computer opponents). Moreover, participants submitted lower bids when they experienced higher levels of overall arousal. What is striking is that the relationship between overall arousal and bidding behavior was only present in the high-agency condition. In the low-agency condition, in contrast, bids and overall arousal levels were lower—and uncorrelated. Additionally, we observed participants' immediate emotions *in response* to auction events. Again, we found that participants exhibit stronger reactions in the high-agency condition. This is the first paper to study the interplay of agency, immediate emotions, overall arousal, and economic behavior (bidding).

This paper proceeds as follows. In Section 2, we outline the study's theoretical background and hypotheses. In Section 3, we outline the experimental design. In Section 4, we analyze the bidders' immediate emotions in response to discrete auction events and the interplay of agency, overall arousal, bidding behavior, and market efficiency. Finally, in Section 5, we discuss the study's theoretical and managerial implications and present our conclusions.

2. Theoretical Background and Hypotheses

Over the past decade, the presence of computerized agents has become pervasive in everyday life (Fox, An, & Janssen, forthcoming). Where humans traditionally directly interacted with other humans, many users today interact with computerized agents. Thus, the domain of cooperative and competitive interactions has been extended from a purely human environment to a "mixed zone" in which sentient human beings and artificial agents interact. The range of experiences is captured by the notion of agency, which is the extent to which users believe that they are "interacting with another sentient human being" (Guadagno, Blascovich, Bailenson, & McCall, 2007, p. 3). Thereby, settings in which users knowingly interact with computerized agents yield *low agency*, whereas settings in which users knowingly interact with other humans yield *high agency* (Guadagno et al., 2007).

While computer agents now also play an increasingly important role in electronic auctions (Ariely et al., 2005; Brogaard et al., 2014), research on the impact of computer agents on the human bidders' affective processes and behavior is scant. As such, with this paper, we contribute to an improved understanding of affective processes and behavior in electronic auctions by building on established research on the role of agency in different contexts of human-computer interaction. This research has shown that agency has a definite influence on users' affective processes and behavior, which, in turn, depends on (among other factors) the type of the task and the computer agents' behavioral realism (Blascovich et al., 2002; Fox et al., forthcoming; Guadagno et al., 2007; Lim & Reeves, 2010)[1]. In particular, while researchers have found that agency has an influence in the domain of *communicative tasks* (e.g., persuasive communication (Guadagno et al., 2007; Guadagno, Swinth, & Blascovich, 2011), self-introduction (Nowak & Biocca, 2003; von der Pütten, Krämer, Gratch, & Kang, 2010,) and chatting (Appel, von der Pütten, Krämer, & Gratch, 2012)) and *cooperative* tasks (e.g., trading items (Lim & Reeves, 2010), bargaining (Sanfey, Rilling, Aronson, Nystrom, & Cohen, 2003), and trust games (Riedl, Mohr, Kenning, Davis, & Heekeren, 2014b)), this influence seems to be even more pronounced in *competitive* tasks (Gallagher, Jack, Roepstorff, & Frith, 2002; Lim & Reeves, 2010; Polosan et al., 2011; Williams & Clippinger, 2002). In the context of computer games, for instance, Lim and Reeves (2010) found that the differences in affective processes between high- and low-agency settings were particularly strong in competitive rather than cooperative interaction.

Because auctions are characterized by an inherent "social competition" (Delgado, Schotter, Ozbay, & Phelphs, 2008, p. 1849) and, thus, fall into the category of competitive tasks, we expect that agency also plays an important role in electronic auctions. In our study, we employ first-price sealed-bid (FPSB) auctions to investigate the role of agency. In FPSB auctions, each bidder submits one single bid without knowing the respective other bids, the highest bid wins the auction, and the winning bidder pays a price in the amount of their bid (Engelbrecht-Wiggans & Katok, 2008; Vickrey, 1961). Classical auction theory assumes that bidding in an auction can essentially be understood as a maximization of expected utility. In contrast, our study starts from the intuition that (1) bidding in an electronic auction also involves affective processes (i.e., experiencing intense immediate emotions

[1] In the literature, researchers who investigate agency often also consider the influence of the counterpart's graphical representation (e.g., Nowak & Biocca, 2003; Appel et al., 2012; Riedl et al., 2014b; Fox et al., forthcoming). Because, one of the features of online auctions is that the parties "remain anonymous and transactions between parties are of an impersonal nature" (Steinhart, Kamins, Mazursky, & Noy, 2013, p. 48), we deliberately focus on the role of agency in an environment without graphical representations. We come back to this aspect in more detail in Section 5.

such as the joy of winning and the frustration of losing (Astor, Adam, Jähnig, & Seifert, 2013; Delgado et al., 2008; Ding, Eliashberg, Huber, & Saini, 2005) and competitive arousal (Ariely & Simonson, 2003; Ku, Malhotra, & Murnighan, 2005)), and that (2) these processes are influenced by agency. With respect to affective processes, we are particularly interested in bidders' *immediate emotions* (i.e., short-lived subjective experiences) (Rick & Loewenstein, 2008) in response to specific auction events (Astor et al., 2013) and the bidders' *overall arousal* (i.e., the intensity of the overall emotional state) during the auction process (Ku et al., 2005).[2]

Thereby, we build on the advances in neuroIS (Dimoka, Pavlou, & Davis, 2011; Riedl et al., 2010; Riedl et al., 2014a; vom Brocke & Liang, 2014; vom Brocke, Riedl, & Léger, 2013) by using SCR measurements to assess the intensity of immediate emotions and HR measurements for overall arousal. NeuroIS research has demonstrated that these measures can provide novel insight into users' affective processes interacting with information systems. In particular, researchers have recently used SCR measurements to investigate computer users' immediate stress reactions (Riedl, Kindermann, Auinger, & Javor, 2013) and used HR measurements to investigate users' overall arousal in the context of IS use patterns (Ortiz de Guinea & Webster, 2013) and enterprise resource planning systems (Ortiz de Guinea, Titah, & Léger, 2013).

In summary, we investigate the interplay of agency, the bidders' affective processes, and bidding behavior in an integrated approach. Figure 1 depicts our research approach. We outline the underlying theoretical concepts and hypotheses in detail in Sections 2.1 to 2.3. We summarize and structure related literature, specifically concerning experimental studies on the impact of agency on human affective processes and behavior, in Table 1 at the end of this section.

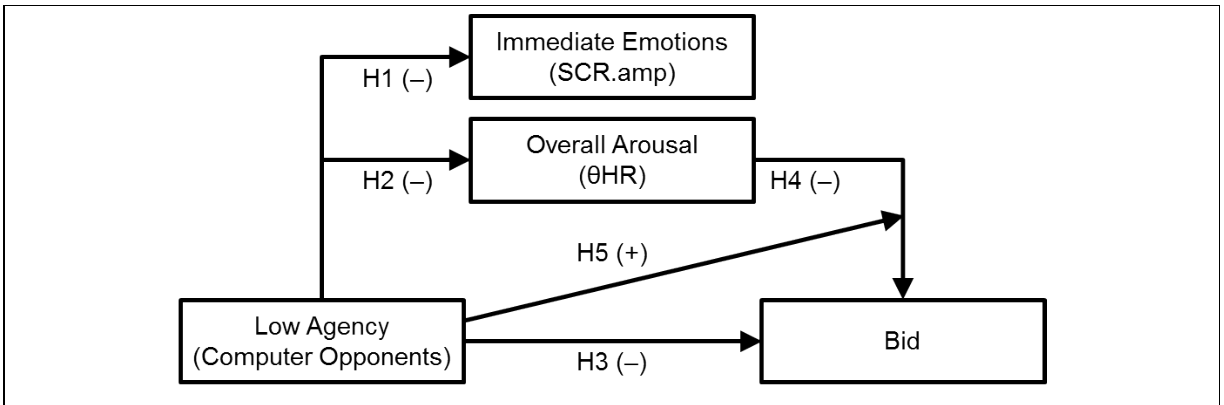

Figure 1. Research Model

2.1. The Impact of Agency on Immediate Emotions and Overall Arousal in Electronic Auctions (H1 & H2)

From an evolutionary psychology perspective, engaging in cooperative and competitive interaction with other conspecifics has always been an important factor in survival and overall human success (Decety, Jackson, Sommerville, Chaminade, & Meltzoff, 2004; Loch, Galunic, & Schneider, 2006). To succeed in social interactions, humans have developed a wide range of strategies, which are based both on cognitive (e.g., analytical and logical reasoning, perspective taking) and affective processes (e.g., immediate emotions, overall arousal). Because the "human brain developed at a time when only human beings were able to show social behavior", these processes inherently have a strong focus on human counterparts (von der Pütten et al., 2010, p. 1642). To assess and predict others' intentions, beliefs, and behaviors, humans make inferences about their counterparts' mental states—a core human ability commonly referred to as "mentalizing" (Decety et al., 2004; Frith & Frith, 2006) or "theory of mind" (Polosan et al., 2011).

[2] The term *arousal* can be used to describe both the intensity of immediate emotions *(phasic arousal)* and the intensity of the overall emotional state *(overall arousal)*. To avoid such ambiguity, we use the term *arousal* only to refer to overall arousal in this paper.

Mentalizing is the “ability to read the mental states of other agents” (Frith & Frith, 2006, p. 531). Gallagher et al. (2002) established that the anterior paracingulate cortex, a brain region repeatedly found to be activated when humans think about mental states (Frith & Frith, 2006), plays a critical role for mentalizing in competitive human-human interaction. The authors employed an online version of the game “stone, paper, scissors” and found that the anterior paracingulate cortex was only activated when participants believed to compete with human rather than computer opponents. The authors concluded that humans adapt an “intentional stance” when competing with humans, which is not the case when competing with computer agents. While mentalizing primarily builds on cognitive processes, such as perspective taking, reflecting on previously acquired knowledge about the world, and anticipating what a person is going to think and feel next, mentalizing also includes affective processes (Frith & Frith, 2006; Lim & Reeves, 2010; Polosan et al., 2011). In particular, humans seek to simulate and reenact their counterparts’ emotions through the brain’s mirror system to assess their affective processes and predict their intentions. As part of this process, the same brain regions are activated “as when we experience the same emotion ourselves” (cf. simulation theory, Frith & Frith, 2006, p. 531). In an electronic auction, for instance, bidders might try to assess their competitors’ affective processes to predict their bids. Even though computer agents can be designed to simulate affective processes and take on the role of “social actors” (Nass & Moon, 2000, p. 84; Zadro, Williams, & Richardson, 2004), one must expect that attempting to reenact the affective processes of computer agents is less pronounced than simulating and reenacting those of human counterparts (Lim & Reeves, 2010; Polosan et al., 2011). As such, we expect affective processes to be weaker when agency is low.

In addition to assessing others’ emotions, social interactions also have a direct influence on our own emotional states. By weighing the consequences of our actions and fostering social interactions, emotions “guide our actions in an adaptive fashion” (Wallin, 2007, p. 136) and enable us to take advantageous decisions (Bechara & Damasio, 2005). As such, emotions are an important element of human decision making, particularly in social interactions. According to social comparison theory, engaging in social interactions with other humans leads to comparing one’s status to others’ (Festinger, 1954). Such social comparisons can fuel overall arousal (Buunk, Collins, Taylor, & Van Yperen, 1990; Lim & Reeves, 2010) and trigger immediate emotions, such as envy and gloating, which serve to keep track of “social status” (Bault, Coricelle, Rustichini, 2008, p. 1). For instance, Bault et al. (2008) investigated how a lottery player’s emotions are affected by the presence of a second player. They found that, when only one of the players could win, the immediate emotions in response to winning and losing are experienced stronger than when there was no second player. Thus, even though the behavior of the second player had no influence on the first player’s payoffs, the second player’s presence introduced a social reference point that was reflected in affective processes.

Computer agents, however, can hardly serve as social reference points. Due to the difference in nature, comparability—as one driver for social comparison processes—is hardly given (cf. Festinger’s (1954) third hypothesis). Also with regard to the evolutionary function of social comparison processes among members of a society, computer agents—even though they can, in fact, be designed to act like social beings and humans, in turn, have even shown social behavior towards computer agents (Nass & Moon, 2000; Zadro et al., 2004)—are yet not equal members of the social sphere in which we live, cooperate, compete, and compare. In view of lacking comparability and social nature, comparing one’s own social status to that of a computer agent is pointless (Engelbrecht-Wiggans & Katok, 2008). Thus, following social comparison theory, overall arousal and the intensity of immediate emotions should be lower when humans interact with computer agents.

Empirical evidence supports this line of argumentation. Sanfey et al. (2003) and Rilling, Sanfey, Aronson, Nystrom, and Cohen (2004), for instance, found that human subjects exhibited weaker activation of brain regions related to emotions when receiving unfair offers from computer opponents rather than from human counterparts. In the context of competitive computer games, Lim and Reeves (2010), Weibel, Wissmath, Habegger, Steiner, and Groner (2008), and Ravaja et al. (2006) found that players experienced less overall arousal when playing competitive games against computer opponents rather than against human opponents. Interacting with humans was also reported to increase players’ enjoyment compared to interaction with computers (Gajadhar, Jack, and Roepstorff, 2008), whereas Williams and Clippinger (2002, p. 503) found that playing a Monopoly game with low agency “generated significantly more aggression in the participants than playing against another person”. Eastin and

Griffiths (2006), however, found no effects of agency on affective processes and behavior in different types of computer games at all. While, in principle, affective processes are essential for all social interactions, they seem to be of particular importance for competitive interaction (Decety et al., 2004; Lim & Reeves, 2010; Weibel et al., 2008); that is, where subjects strive for divergent or even mutually exclusive goals. Here, social comparisons can cause social competition among individuals. Hence, differences in affective processing between low and high agency should be particularly pronounced in competitive scenarios.

In electronic auctions, only one bidder can win the auction while all others lose (Malhotra, Ku, & Murnighan, 2008). Hence, electronic auctions are characterized by an inherent "social competition" (Delgado et al., 2008, p. 1849). During the auction process, this social competition causes increased overall arousal and a "desire to win" (Malhotra et al., 2008). The immediate emotions triggered in response to winning or losing an auction are usually referred to as the joy of winning and the frustration of losing, respectively (Astor et al., 2013; Delgado et al., 2008; Ding et al., 2005)[3]. Naturally, winning or losing an auction may cause emotions regardless of the opponents' type (humans or computers) since, after all, there is money at stake. As we have determined based on mentalizing and social comparison theory, however, competing with computer agents yields important differences to competing with humans. Thus, we hypothesize that affective processes are less pronounced in settings with low agency and that this is also reflected in the physiological correlates of immediate emotions and overall arousal:

> **H1:** *The intensity of bidders' immediate emotions is lower in FPSB auctions with low agency than in FPSB auctions with high agency.*

> **H2:** *The level of bidders' overall arousal is lower in FPSB auctions with low agency than in FPSB auctions with high agency.*

2.2. The Impact of Agency on Bidding Behavior (H3)

Previous research has shown that agency can directly affect behavior (e.g., impairing performance in novel tasks in front of a virtual audience (Hoyt, Blascovich, & Swinth, 2003) or causing different evasive actions when being approached by a virtual character (Bailenson, Blascovich, Beall, & Loomis, 2003)). The lack of an actual social competition in auctions with low agency might, thus, not only affect human bidders' affective processes (cf. H1, H2) but, since it is inherently related to it, also their bidding behavior. In particular, if there is in fact a positive relationship between agency and the intensity of immediate emotions in response to the auction outcome, agency should also affect the utility bidders derive from winning or losing an auction, which, in turn, can lead to a change in bidding behavior[4]. In general, anticipating a joy of winning an auction can be reflected in an additional expected utility and, hence, an extra motivation for winning the auction. In contrast, anticipating a frustration of losing can be reflected in an additional expected disutility and, hence, an extra motivation for not losing (i.e., again, winning the auction). Since these emotions are presumably more intense when there is factual social competition, both mechanisms should cause bidders to place higher bids (van den Bos et al., 2008) in settings with high agency.

In behavioral economics theory, the influence of such social comparisons on the decision makers' utility is captured by other-regarding or social preferences. Such preferences explicitly consider that humans are not only interested in their own individual gains and losses but also in the payoffs of others who serve as social reference points (Bault et al., 2008; van den Bos et al., 2008). Relative payoffs and interpersonal comparisons have been found to play an important role in economic behavior (Fehr & Schmidt, 1999).

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[3] Bidders may also derive negative utility when they experience the "winner's curse"; that is, paying more for an item than it is actually worth because of overestimating the good's true value (Easley, Wood, & Barkataki, 2010). Moreover, depending on the auction and the information provided, a bidder may also experience winner regret and loser regret (Engelbrecht-Wiggans & Katok, 2008). In our experiment, however, we deliberately excluded these information events and bidders knew the exact value of the item. Thus, winner regret, loser regret, and the winner's curse are negligible in our study.

[4] Here, we assume that winning an auction is related to emotions with positive valence and that losing an auction is related to emotions with negative valence (Ding et al., 2005; Delgado et al., 2008; Astor et al., 2013).

Previous research has demonstrated that, due to such interpersonal comparisons (i.e., the "social nature of auctions"; van den Bos et al., 2008), utility derived from succeeding in peer competition may even outweigh the monetary incentives (Cooper & Fang, 2008), which eventually causes auction participants to overbid and pay more for an item than it is actually worth to them (Malhotra et al., 2008). In this sense, high agency causes market interaction to be seen as a "play-to-win game" (Stafford & Stern, 2002, p. 44)[5] in which "people enjoy winning—especially against their rivals—even at a price" (Malhotra et al., 2008, p. 80). Due to this characteristic of auctions, researchers have even identified "the thrill of bidding, the excitement of winning, and the stimulation of beating competitors" as reasons for the popularity of auctions (Lee, Kim, & Fairhurst, 2009b, p. 77). Hence, the source of additional utility or disutility is attributed to auctions' inherent social competition (Delgado et al., 2008). In that sense, bidders do not just buy commodities—they win or lose them against other bidders. Correspondingly, Ariely and Simonson (2003) found in an Internet survey that 76.8 percent of the survey respondents perceived other bidders as competitors and referred to auction outcomes as "winning" and "losing". Palmer and Forsyth (2006, p. 236) concluded that "auction behavior is, thus, a socially constructed behavior".

In auctions with low agency, winning per se is less important because here the social competition does not exist at all or is at least less severe. Hence, we expect bidders to place lower bids in such settings. For the case of common value auctions, for instance, van den Bos et al. (2008) found that agency had a positive effect on bids. Bidders submitted significantly higher bids and were prone to the winner's curse when competing against other humans but not if the opponents were computers. In the context of bargaining, Sanfey et al. (2003) and van't Wout, Kahn, Sanfey, and Aleman (2006) found that humans were more likely to accept unfair offers from computerized agents than from other humans (i.e., showing a higher tolerance towards unfavorable allocations due to lower agency).

As such, we expect agency, associated with its effect on affective processes, to influence bidding behavior. For most bidders, winning an auction against others constitutes value in itself. This value, in turn, depends on the intensity of the social competition (i.e. whether the bidder competes in a setting with high or low agency). Thus, we hypothesize:

> **H3**: *In FPSB auctions with low agency, bidders place lower bids than they do in FPSB auctions with high agency*.

2.3. The Relationship between Overall Arousal & Bidding Behavior (H4 & H5)

Beyond the effect of agency on overall arousal and bidding behavior, we are interested in the relationship between overall arousal and bidding behavior and how this relationship is affected by agency. Previous research has established that both affective and cognitive processes have a definite influence on human decision making (Bechara & Damasio, 2005). Depending on the situation, however, the influence of either affective or cognitive processes on behavior can be more pronounced (Ariely & Loewenstein, 2006). In the literature, the role of affective and cognitive processes in decision making is often conceptualized in "dual system" models where the affective system is characterized as fast, automatic, and emotionally charged, while the cognitive system is characterized as analytic, logical, and abstract (Lee, Amir, & Ariely, 2009a; Steinhart et al., 2013). Clearly, the conceptualization of such dual system models is "undoubtedly an oversimplification and an imprecise representation of the complex human mind" (Lee et al., 2009a, p. 174). The overall distinction of decision making into situations in which either affective or cognitive processes are more pronounced, however, is yet useful for investigating emotional behavior (Lee et al., 2009a). In the following paragraphs, we outline the theoretical basis for the moderating effect of agency on the relation of overall arousal and bidding behavior. We argue that, because affective processes are expected to be less intense in low agency auctions, the relationship between overall arousal and bidding behavior should be weaker when agency is low. We start by discussing traditional settings with human counterparts and, thus, high agency.

[5] Correspondingly, in 2007, eBay launched an advertisement campaign called "shop victoriously" that stressed the competitive nature of auctions with the slogan "It's better when you win it!" (eBay.com, 2007). In addition, the platform sends emails to users when another user has taken over the status as currently leading bidder for a specific good from them that suggests to hit back with an even higher bid.

2.3.1. High Agency

For such settings, researchers commonly recognize that human financial decision making tends to rely on affective processes more strongly when decision makers experience higher levels of overall arousal (Peterson, 2007). Slovic, Funicane, Peters, and MacGregor (2007) argue that humans seem to follow an “affect heuristic” that guides their decision making through affective processes triggered by internal and external stimuli. As human bidders are expected to experience higher overall arousal levels in the social competition of auctions with high agency (cf. H2), the assumption of affect heuristics suggests a marked relationship between overall arousal and bidding behavior for high-agency scenarios.

Previous research has found that the relationship between arousal and decision making is twofold. On the one hand, situations involving risk are known to trigger arousal because they can have material consequences for the decision maker (Trimpop, 1994). On the other hand, arousal can also cause an increased willingness to take such risks to achieve higher rewards (Ariely & Loewenstein, 2006; Rivers, Reyna, & Mills, 2008). The perspective of evolutionary psychology provides a rationale for this because “most appetitive systems in the brain, including hunger and thirst, are designed to increase motivation during times of opportunity” (Ariely & Loewenstein, 2006, p. 88). This insight suggests a negative relationship between arousal and bids because arousal enhances the motivational effects of rewards (Rivers et al., 2008). Higher rewards or the chance on higher rewards can usually only be realized by either higher levels of effort or by taking more risk, respectively. For FPSB auctions with money at stake, arousal may be interpreted as a cue for the chance of making a profit, which is amplified and results in striving for winning an even higher amount. One can only increasing their potential profit (value of the good minus price paid) in a FPSB auction by submitting lower bids, which concurrently entails a lower probability of winning the auction (Vickrey, 1961)[6]. Thus, lower bids may actually be caused by higher levels of arousal.

The above reasoning speaks in favor of a negative relationship between arousal and bid height. There are, however, also dissenting theoretical approaches. According to the competitive arousal model, competitive environments fuel individuals’ desire to win in a two-step process (Ku et al., 2005, Malhotra et al., 2008). First, factors such as rivalry, time pressure, or social facilitation induce higher overall arousal levels. This higher arousal then fosters the desire to win against the opponent, which supersedes the original goal (for instance, generating the highest possible expected profit) and, by this means, affects bidding behavior. Since higher bids are ceteris paribus more likely to win an auction than lower bids, the competitive arousal model suggests a positive relation between arousal and bid height.

However, ample evidence exists for the prior line of thought that stresses the enhancing power of arousal on the motivational effects of rewards. Thus, the empirical observations speak in favor of a negative relationship between arousal and bid height (Ariely & Loewenstein, 2006; Mano, 1994; Trimpop, 1994). Mano (1994), for instance, investigated the impact of arousal on the willingness-to-pay for lotteries and insurances and found that higher arousal was related to a higher attraction to the possible rewards associated with playing a lottery. Moreover, Rivers et al. (2008) reviewed decision making under the influence of different factors such as age, impulsivity, and arousal and found arousal to be an impulsivity-promoting factor. Ariely and Loewenstein (2006) show that (sexual) arousal is capable of increasing individuals’ subjective willingness to engage in unsafe ventures.

Thus, taken as a whole, the theoretical perspective on arousal and bidding suggests a negative relation between arousal and bids for high agency scenarios. Therefore, we hypothesize that higher levels of arousal are associated with lower bids in FPSB auctions:

> **H4:** *In FPSB auctions with high agency, higher overall arousal levels are related to lower bids.*

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[6] This particularly holds for auctions in which bidders know their exact valuation of the auctioned off commodity (e.g., independent private values). In other scenarios, as, for instance, in common value auctions, one also faces the danger of paying too much and experiencing the winner’s curse (Easley et al., 2010). In our study, however, the bidders know the valuation and, thus, the winner’s curse is not possible.

2.3.2. Low Agency

While the tense atmosphere of socially competing with humans establishes a context that possibly pronounces the role of affective processes (see H1, H2, and H4), we also have reason to believe that the working principles of linking arousal and bidding behavior are different for low agency. First, because we can expect bidders' affective processes to be less intense in auctions with low agency overall, relying on such lower impulses can be expected to play a less important role, too. Second, decision makers tend to rather rely on cognitive processes in "depersonalized" and "asocial" situations (Stanovich & West, 2000). As we outline above, researchers have often attributed arousal directly to auctions' social competition. In absence of an actual social competition in auctions with computer agents, the bidders might, thus, focus on rational, analytical thinking. Based on this reasoning, we conjecture that low agency attenuates the relationship between arousal and bids.

Previous research provides support for the argument that the social context de facto plays an important role in the relationship between arousal and behavior. Sanfey et al. (2003), for instance, considered ultimatum bargaining and found that unfair offers by humans induced stronger activation in the anterior insula (interpreted as the perception of negative emotions) than did those of computer agents and that computerized agents rejected humans' unfair offers more often than identical unfair offers. Sanfey et al. do not explicitly state the effect of agency on the relation between arousal and behavior, but one can assume that the gradient between arousal and rejection rates is steeper for high agency. In a follow-up study, van't Wout et al. (2006, p. 565) further investigated this matter by considering the interplay of agency, arousal, and economic decisions in ultimatum games. The authors found a significant correlation between arousal and rejection rates for human offers, whereas there was, in fact, no such effect for computer offers (on subject level). Put differently, for human offers, acceptance was related to low skin conductance levels, whereas rejection was related to high ones. For computer offers, both acceptance and rejection showed intermediate and similar skin conductance levels.

Based on the above reasoning and empirical indication, we hypothesize that the presence of computer agents mitigates the relationship between arousal and bids:

> **H5:** *The relationship between overall arousal and bids is mitigated by low agency.*

Table 1. Related Literature on the Impact of Agency on Affective Processes and Behavior

Authors (year)	Task, Description	Dependent Variables	Independent Variables	Mediator, Moderator, and Control Variables	NeuroIS Method	VL	Coop	Comp	GR	$	#
Gallagher et al. (2002)	Playing stone, paper, scissors against a computer / a human; guessing the others choice	Anterior paracingulate cortex, inferior frontal cortex, and cerebellum activation	Framing towards mentalizing/ rule solving	-	fMRI			X			9
Williams & Clippinger (2002)	Playing Monopoly against human/ computer opponents, within subject design	Aggression	Human/ computer opponents	-	-	X		X		X	54
Bailenson et al. (2003)	Approaching a character in a virtual environment	Distance to virtual character, social presence, affect, memory	Participant gender, agency, virtual character gender, gaze behavior	-	-		X		X		80 80
Hoyt et al. (2003)	Social facilitation and social inhibition in pattern recognition and categorization tasks in a virtual environment	Task performance	Perceived agency of virtual observers (agents, avatars, none), task type (novel, well-learned)	Mediator: co-presence, control: task novelty/anxiety	-						39
Nowak & Biocca (2003)	Present oneself, describe skills, get to the partner; effect of agency and anthropomorphism on various measures of presence	Presence, co-presence, social presence	Anthropomorphism, perceived agency	-	-		X		X		134

Table 1. Related Literature on the Impact of Agency on Affective Processes and Behavior (cont.)

Authors (year)	Task, Description	Dependent Variables	Independent Variables	Mediator, Moderator, and Control Variables	NeuroIS Method	VL	Coop	Comp	GR	$	#
Sanfey et al. (2003)	Responding to offers in an ultimatum bargaining game; different offers (fair/unfair) and Proposers (human/ computer)	Economic/ behavioral response (acceptance rate); perception of fairness, bilateral anterior insula, dorsolateral prefrontal cortex	Fairness of offer, type of co-player (human/ computer), acceptance rate	-	fMRI	X	X			X	19
Rilling et al. (2004)	Ultimatum Game and Prisoners' Dilemma with human/ computer partners	Behavior, brain activity	Human/Computer partners, type of offer	-	fMRI		X			X	19
Zadro et al. (2004)	Ball toss game, 2 x 2 between subject (design ostracism/ inclusion x human/ computer co-players)	Levels of belonging, control, self-esteem, meaningful existence, mood	Ostracism/ inclusion, human/ computer co-players, scripted/ unscripted behavior	-	-	X					62 77
Eastin & Griffiths (2006)	Hostility and presence in different forms of computer games among male players	Hostility, presence	Game type (fighting, shooting, driving), human/ computer opponents, virtual reality/ standard console	-	-			X			219
Mandryk et al. (2006)	Playing a sports computer game under 1) different levels of difficulty, 2) against a friend/computer	Boredom, frustration, fun, ease, engagement, challenge, excitement	Opponent (friend/ computer), difficulty (beginner, easy, medium, difficult)	-	HR, SCR, R	X		X			8 10

Table 1. Related Literature on the Impact of Agency on Affective Processes and Behavior (cont.)

Authors (year)	Task, Description	Dependent Variables	Independent Variables	Mediator, Moderator, and Control Variables	NeuroIS Method	VL	Coop	Comp	GR	$	#
Ravaja et al. (2006)	Effects of different opponent types on spatial presence, emotional responses threat and challenge appraisals	Anticipated threat, challenge, spatial presence, arousal (HR), engagement, valence, arousal (all self-reported)	Nature of opponent (computer, friend, stranger)	-	HR	X		X			33
van t Wout et al. (2006)	Responding to offers in an ultimatum bargaining game; different offers (fair/ unfair) and proposers (human/ computer)	SCR, perception of fairness, Economic/ behavioral response (rejection rate)	Human/ computer offers	-	SCR		X			X	30
Guadagno et al. (2007)	Listen to & evaluate communication agent/avatar in a virtual environment; effect of gender, behavioral realism	Perceived realism, attitude change, agent liking and credibility, quality of presentation	Virtual gender (m/ f), participant gender (m/ f), behavioral realism (h/ low)	-	-		X		X		65 174
Gajadhar et al. (2008)	Playing WoodPong against human/ computer opponents	Game experience, aggression state	Social setting (virtual, mediated, co-located), familiarity (friends/ strangers), Performance (winners/losers)	Mediator: social presence	-	X		X			42
van den Bos et al. (2008)	Winners curse in electronic auctions	Bids	Agency	-	-			X		X	47 48

Table 1. Related Literature on the Impact of Agency on Affective Processes and Behavior (cont.)

Authors (year)	Task, Description	Dependent Variables	Independent Variables	Mediator, Moderator, and Control Variables	NeuroIS Method	VL	Coop	Comp	GR	$	#
Weibel et al. (2008)	Playing online games against computer- vs. human-controlled opponents	Participants' feelings of presence, flow, and enjoyment	Type of opponent (human/ computer)	Control: age, gender, effort while playing, time spent playing computer games	-			X			70
Lim & Reeves (2010)	Fight/ trade in World of Warcraft; agency (avatar, agent) and type of interaction (competition, cooperation)	Arousal (HR, SCL) and emotions (SCR), valence, presence, liking the co-player	Agent/ avatar, cooperation/ competition	-	HR, SCL, SCR	X	X	X			32
von der Pütten et al. (2010)	Answering questions to a conversational agent; effect of agency/ behavioral realism on social presence and emotional state	Social presence, emotional state (PANAS), rapport, perception of virtual character, #words, pos./neg. affect	Agency (agent/ avatar), behavioral realism (showing feedback behavior/ no behavior)	-	-		X		X		83
Guadagno et al. (2011)	Smiles/ no smiles and agency. Task: talk to a counselor in a virtual environment	Counselor empathy	Agency, smiling	Moderator: interaction partner type (agency)	-		X		X		38
Polosan et al. (2011)	Playing a competitive version of the Stroop task against different opponents (human/ computer)	superior and middle frontal, anterior cingulate, insula and fusiform gyrus	Agency, word congruence	-	fMRI			X			14

Table 1. Related Literature on the Impact of Agency on Affective Processes and Behavior (cont.)

Authors (year)	Task, Description	Dependent Variables	Independent Variables	Mediator, Moderator, and Control Variables	NeuroIS Method	VL	Coop	Comp	GR	$	#
Appel et al. (2012)	Text-chat with another participant, effect of agency/ social cues	PANAS, person perception, rapport, social presence, #words, revealed characteristics	Agency (agent/ avatar), number of social cues	-	-		X		X		90
Riedl et al. (2014)	Playing a trust game with a human/ computer partner; assessing trustworthiness	Money transfers, trustworthiness prediction, medial frontal cortex activation, learning rates	Human/ avatar pictures; trustworthiness	-	fMRI		X		X	X	18
This study	Impact of computerized agents on overall arousal, immediate emotions and bidding behavior in electronic auctions	Bids, immediate emotions, overall arousal	Agency	Mediator: overall arousal; moderator: agency; control: risk aversion, gender, IPV	HR, SCR			X		X	103

Note: VL: valence; COOP: cooperative; COMP: competitive; GR: graphical representation; $: monetary incentives; #: number of observations; SCL: skin conductance; SCR: skin conductance response; HR: heart rate; R: respiration.

3. Experimental Design

Our experiment included two treatments. First, in the high agency (HA) treatment, the participants interacted with only human opponents. Second, in the low agency (LA) treatment, the participants interacted with only computerized opponents only. The computerized bidders in the LA treatment replicated the bids of the human bidders. We conducted the LA treatment sessions one week after the HA treatment sessions. By replicating the human bids, we avoided influencing the results due to differences in bidding by the agents, which makes the results comparable across treatments (see van den Bos et al. (2008) for a similar approach). Thus, participants in the LA treatment faced the exact same bids from their opponents as participants in the HA treatment. Therefore, the only difference between treatments is that bidders knew that they were interacting with human opponents (HA) or computer opponents (LA). The bidders were not represented graphically. Also, to avoid order effects, we based our experiments on a between-subjects design (i.e., subjects either participated in the HA or LA treatment but not both).

During the experiment, each bidder took part in a sequence of 30 FPSB auctions with two other bidders. The FPSB auction was particularly suited for our study because (1) it belongs to the class of static auctions and, thus, allowed us to maintain a high level of control with little path dependence, (2) we could investigate the impact of computerized agents in a scenario with little interaction, and (3) the FPSB auction format is frequently used in markets worldwide. In the HA treatment, we randomly reassigned participants to groups of three bidders before every single auction period (random stranger matching). Thus, a subject did not know which other participants were currently participating in the same auction. Each group then played a single FPSB auction independently with three bidders (see Engelbrecht-Wiggans & Katok (2008), Katok & Kwasnica (2008), and Astor et al. (2013) for similar approaches). After each period, we rematched the participants into different groups of three, which we communicated in the instructions so that participants could not gain insights about specific participants and carry them over to the next interaction with a specific participant. In the LA treatment, we matched every participant with two computerized bidding agents, which replicated the human bids from the HA treatment one week earlier. Here also, we rematched every participant into a different group with two computerized bidding agents after each auction period.

3.1. Auction Process

Before an auction began, the system informed each bidder i about their independent private value (IPV) v_i for the commodity to be auctioned[7]. This IPV was independently drawn for each bidder from a uniform distribution with support on the discrete integer interval {11, 12, …, 109, 110} and is expressed in monetary units (MU). The bidders only knew that there were three bidders in each auction, their own IPV, and the general distribution of IPVs, which was the same for all bidders. We denote the bid of participant i by b_i. The winning bidder i received a payoff equal to the winning bid minus their individual valuation for the commodity being auctioned ($v_i - b_i$). All other bidders received a payoff of zero. The equilibrium bidding strategy $b(v_i)^*$ for bidder i in an auction with three risk-neutral bidders in total and the common distribution of IPVs denoted above is given by $b(v_i)^* = (2/3) * (v_i - 10) + 10$ (Krishna, 2002).

To exclude missed-opportunity and money-left-on-the-table effects (Engelbrecht-Wiggans & Katok, 2008), we presented the bidders with a minimal information environment in which they were neither informed about the highest nor the second-highest bid (van den Bos et al., 2008). At the end of an auction, bidders only received information on whether they had won the auction or not and their payoff. We did not reveal the bidders' identities. To capture the physiological reactions to specific events throughout the auction process, we provided information in timed intervals of at least five seconds (Sanfey et al., 2003). In particular, we investigated the intensities of the bidders' immediate emotions in response to three specific events in the auction process (E1, E2, and E3).

[7] The IPV model dates back to the seminal work of Vickrey (1961) and is frequently used in auction experiments (see Katok and Kwasnica (2008), Engelbrecht-Wiggans and Katok (2008), and Astor et al. (2013) for similar approaches). An IPV corresponds to a bidder's individual valuation of the auctioned commodity. This is *private* information (i.e., a bidder only knows their own IPV but not the IPVs of the other bidders) and the valuation is *independent* (i.e., knowing one's own IPV provides no additional information on other bidders' IPVs). The bidder then has to weigh their chances of winning against the nominal payoff in case of winning the auction, which is based on their own IPV and the available information on the distribution of the other bidders' IPVs.

More specifically, we first assessed the bidders' physiological responses to placing a bid (E1). Then, the bidders saw an information screen that informed them that the auction outcome would be revealed soon (E2). Finally, the bidders found out whether they had won or lost the auction (E3). Figure 2 summarizes the auction process.

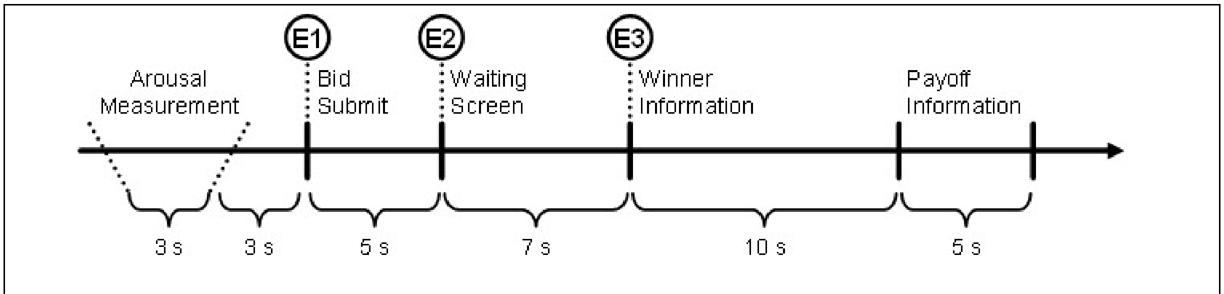

Figure 2. Auction Process and Timed Intervals Between Auction Events

3.2. Procedure

Altogether, 27 female and 93 male participants (six participants per session, 120 in total, mean age = 23.16 years) participated in 20 sessions. There were 12 sessions in the HA treatment, and eight sessions in the LA treatment (N_{HA} = 72, N_{LA} = 48). We conducted the experiment at the Karlsruhe Institute of Technology and in accordance with the university's ethics guidelines. We implemented it by using the z-Tree environment (Fischbacher, 2007). We recruited the participants from a pool of undergraduate students by using the ORSEE software environment (Greiner, 2004). We offered no lump sum payment. The experimental currency was monetary units (MU) with 16 MU being equivalent to €1.00. Depending on the bidders' individual performance, all of the gains and losses accumulated during the auctions went to their individual accounts, which we individually paid out in cash to the participants at the end of the experiment. The average payment was €16.13 (minimum = €5.88, maximum = €28.44).

At the end of each session, we conducted the risk-aversion task by Holt and Laury (2002) to assess each participant's general attitude towards taking risk. We include the recorded value as a control variable that takes the value 1 if a participant is risk-averse and 0 otherwise. In this task, participants could earn up to an additional €3.85. Each participant selected one of two lotteries from 10 different specifications each with a different level of risk and expected payoff. Based on how often participants chose the less-risky lottery, we classified them as risk averse or not risk averse.

Before the first auction started, we introduced a five-minute resting period for calibration purposes (Riedl et al., 2014a). To ensure the participants comprehended the experiment's rules, the participants then had to successfully complete a quiz regarding the experimental instructions and performed five practice auctions in which they did not consider gains and losses. To avoid artifacts due to body movements, we limited participants' interactions with the experimental system to mouse inputs (i.e., they used only their dominant hand). We equipped participants with a pair of earmuffs to avoid the influence of background noise.

During the experiment, we continuously measured the bidders' HR and SCR. We derived HR from an electrocardiogram (ECG) recording device and used a lead I method with single-use electrodes placed on the left and right wrist (Berntson, Quigley, & Lozano, 2007). We recorded skin conductance by using a constant current amplifier measurement system and Ag/AgCl (silver/silver chloride) electrodes. We attached the electrodes to the thenar and hypothenar eminences of the palm of the non-dominant hand with standard electrodermal activity (EDA) electrode paste (Fowles et al., 1981). We conducted all the sessions within a period of two weeks with an average relative humidity of 53.1 percent and an average room temperature of 24.1°C (75.4°F). These values comply with the methodological recommendations of the Society for Psychophysiological Research (Fowles et al., 1981). We had to remove the physiological measurement results of 17 participants from the data sample because the values of either the SCR or HR measurements were outside the range of the measurement system or because of too much noise on the signal. Thus, we analyze a data sample of 120 – 17 = 103 participants (N_{HA}=64 (51 male, 13 female), N_{LA}=39 (29 male, 10 female)). We analyze allocation efficiency, however, based on an auction level and, therefore, include the bids of all 120 participants.

3.3. Physiological Measures

The two correlates used in our study, HR and SCR, are proxies for activation of the autonomous nervous system (ANS) and provide insight into the bidders' affective processes during the auctions. Note that there are further neuroIS measures available that can provide valuable insight into bidders' affective processes, such as fMRI, electroencephalography, electromyography, pupil diameter measurement, and others (Dimoka et al., 2011; Riedl et al., 2014a; vom Brocke & Liang, 2014). While each of these approaches has distinct advantages, we focus on HR and SCR because these measures (1) provide insights into participants' immediate emotions and overall arousal; (2) require little measurement overhead and can, thus, be assessed for several participants simultaneously, which is a necessary prerequisite for interactive economic experimentation; and (3) are measurable unobtrusively because they do not demand electrodes attached to the face or the scalp (such as with electroencephalography, electromyography, startle reflex), so that participants can better focus on the experimental tasks and act in a more habitual way.

HR is a measure that reflects the activity of both the sympathetic and parasympathetic branches of the ANS (Berntson et al., 2007). In this study, we measure HR in beats per minute and use it as a proxy for the overall arousal of the participants before they place a bid. In particular, we use the bidders' average increase in HR (θHR) six to three seconds before they placed a bid relative to the individual baseline level of HR during the five-minute resting period (see Smith and Dickhaut (2005) and Adam, Krämer, and Weinhardt (2012) a similar approach). Thus, an arousal parameter of x% in this context means that a participant's HR in the time frame of six to three seconds *before* submitting a bid was on average x% higher than in the initial calibration phase. This normalization makes θHR comparable across participants and treatments. We do not include the last three seconds before bid submission in computing θHR because previous research has found that participants exhibit deceleratory HR responses in this time frame due to their preparing for imminent action (Jennings, van der Molen, & Brock, 1990).

In contrast, SCR is a measure that directly reflects only the activity of the sympathetic nervous system (Bechara & Damasio, 2005; Dawson, Schell, & Courtney, 2011). Skin conductance is measured in microsiemens (µS) and can be broken down into tonic and phasic components. The tonic component reflects the general arousal level of the individual (skin conductance level, SCL); that is, the ongoing emotional state. In comparison to θHR, however, changes in SCL are rather inert, and, thus, we concentrate on θHR as a proxy for overall arousal. The phasic component of skin conductance represents short monophasic bursts of sympathetic activity (skin conductance response, SCR), which are usually elicited by an external or internal stimulation. Researchers have identified the amplitude of an SCR (SCR.amp) as a proxy for the intensity of immediate emotions and reflects short bursts of sympathetic activity (Dawson et al., 2011). In this study, we obtained the SCR.amp values by decomposing skin conductance into its tonic and phasic components with the Ledalab analysis software (Benedek & Kaernbach, 2010). We used only amplitudes that occurred one to three seconds after each event and amplitudes greater than or equal to a value of .01 µS (Fowles et al., 1981). Following the recommendation of Venables and Christie (1980), we transformed all the SCR.amp values by *log(x+1)*.

4. Results

In this section, we present the results of our study. First, we investigate the intensities of immediate emotions in response to discrete auction events (H1) and then continue with the bidders' overall arousal levels (H2). Subsequently, we analyze the interplay of agency, overall arousal, and bidding behavior (H3-H5). Finally, we expand on the impact of agency on allocation efficiency.

4.1. Immediate Emotions during the Auction Process (H1)

In this section, we consider subjects' SCR.amp as a measure for immediate emotions in response to three discrete auction events: bid submission (E1), an intermediate information screen (informing subjects that the result is about to be displayed) (E2), and the auction outcome (E3). In our research model, we hypothesize that the intensities of such immediate emotions are mitigated when agency is low (H1). In the analysis, we additionally consider the impact of the IPV and the outcome role (winning or losing). For illustration, we group the IPV values into five categories, which Table 2 summarizes.

Table 2. Value Classes

Value class		Value interval	
		Lower bound	Upper bound
0	very low	11	30
1	low	31	50
2	medium	51	70
3	high	71	90
4	very high	21	110
Total range		91	110

Figures 3, 4, and 5 display the bidders' average SCR.amp in response to the three auction events E1, E2, and E3. We group the results by value class and treatment. All of the figures indicate that emotional intensity was generally lower in the low-agency treatment and generally higher for higher value classes. The auction outcome (E3) triggered the strongest responses, whereas E1 and E2 triggered less-intense responses. To confirm the graphical evidence, we conducted four generalized least squares (GLS) regressions in which we modeled each bidder's SCR.amp in response to E1, E2, and E3. We used a between-subjects design as is common in experimental setups, which means that we compared the results of a group of subjects in one group to a different set of subjects in our control group. We sampled the same participants in the same treatment multiple times and accounted for level differences using control variables (gender and risk-aversion). We treated our subjects with two levels of agency; unfortunately, we could treat our subjects with every possible level of agency, and, therefore, we estimate a model that includes random effects to account for this. We estimated a GLS mixed-model that simultaneously accounted for both random effects and fixed effects. We conducted the regressions for each auction by using robust standard errors clustered by subject. For all events, we accounted for the treatment (LA: 1, HA: 0), risk aversion (1: risk averse, 0: not risk averse), sex (female: 1, male: 0), value class (coded as 0 to 4, squared), and arousal before bid submission (θHR). Note that specification (3) includes a dummy for the outcome role (winning: 1, losing: 0), while specification (4) additionally includes the interaction term value class x auction outcome.

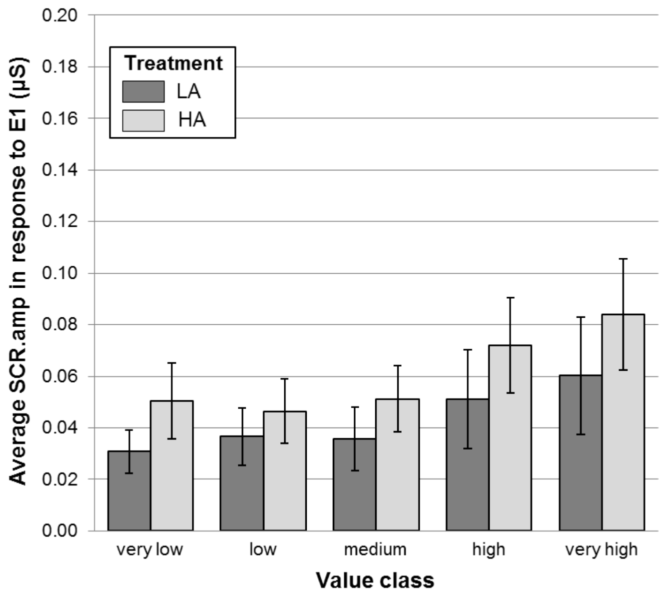

Figure 3. Average SCR.amp in Response to E1

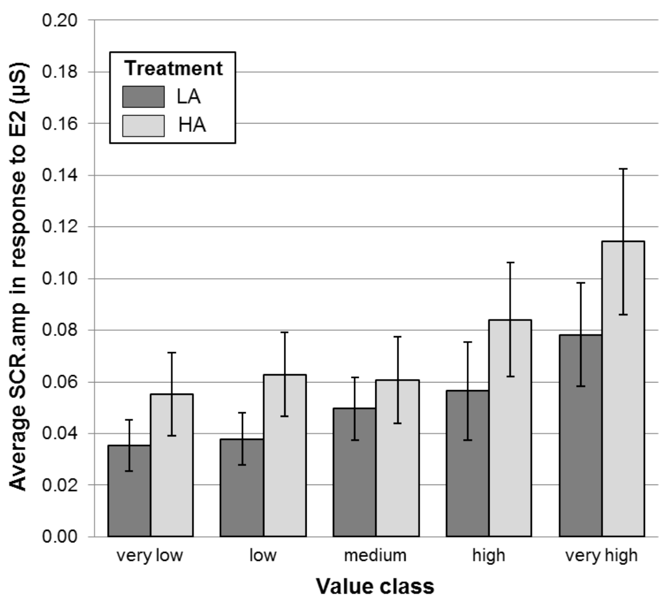

Figure 4. Average SCR.amp in Response to E2

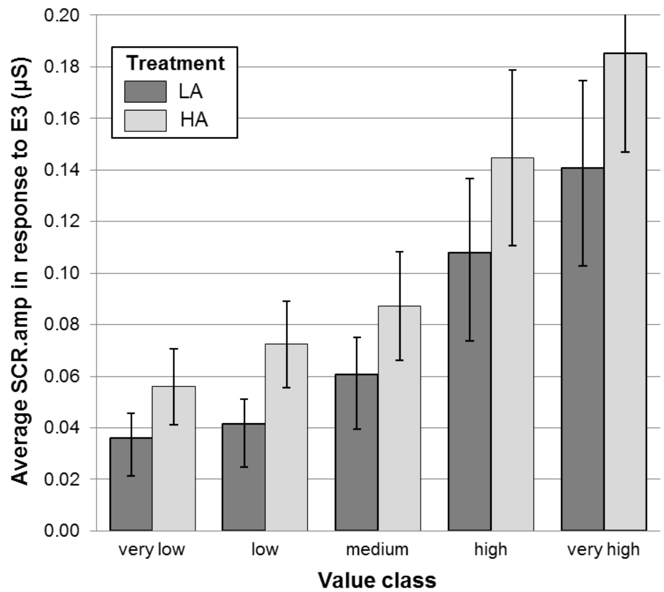

Figure 5. Average SCR.amp in Response to E3

Table 3 summarizes the results of the GLS regressions[8]. First, the general positive relationship between stakes and emotional intensity is confirmed in this setting. The coefficient of value class was positive, significant, and consistent for E1-E3. Thus, the intensity of the bidders' immediate emotions in response to salient auction events was higher for higher value classes. Second, emotions were stronger when bidders experienced higher levels of overall arousal (θHR). In other words, there was a positive relationship between overall arousal and the intensity of immediate emotions, which was consistent for E1-E3. Third, the differences in the intensities of the emotional responses between the LA and HA treatments were significant and consistent for E1-E3 (E1: *b=-.015, p=.084*; E2: *b=-.022, p=.017*; E3: *b=-.030, p=.023*), whereat the effect at E3 was stronger than at E1 and E2. Note, however, that the coefficient was only marginally significant for E1. In summary, our results support H1. The intensity of the bidders' immediate emotions in response to salient auction events was lower for low agency than it was for high agency.

With respect to the impact of outcome role on immediate emotions in response to E3, note that the bidders could lose money in our setting. Thus, the status quo was maintained when an auction was lost, whereas a gain was realized when an auction was won. Thus, one could expect a stronger emotional response to winning rather than losing an auction. The results of specification (3) confirm this conjecture. The coefficient on the dummy variable *winner* was positive and significant (*b=.020, p=.004*). Hence, the intensity of the bidders' immediate emotions in response to the auction outcome was higher if the auction was won. As Figure 6 depicts, the general intensity of emotions in response to E3 was higher in the HA treatment and the responses were stronger for winning an auction.

We did not observe an interaction effect between treatment and auction outcome. Winning an auction (compared to losing) caused stronger responses across both treatments, and participants in the HA treatment showed stronger responses to both winning and losing the auction than the participants in the LA treatment. Interestingly, however, winning an auction in the LA treatment caused stronger responses than losing an auction in the HA treatment. We discuss this point in more detail in Section 5.

[8] Note that, with 103 participants and 30 auctions, a total number of 103 x 30 = 3090 observations would have been possible. In 23 of these 3090 cases, however, we were not able to accurately assess the physiological data for the relevant bidding timeframe due to movement artifacts or due to a sudden noise on the signal. Therefore, the total number of observations was 3090 – 23 = 3067.

Table 3. GLS Regression Models for SCR.amp in Response to the Auction Events E1, E2, and E3

Independent variables	Dependent variables: SCR.amp at different events (E1-E3)							
	(1) E1		(2) E2		(3) E3		(4) E3	
	Beta	Coeff.	Beta	Coeff.	Beta	Coeff.	Beta	Coeff.
Dummy: LA treatment	-.070	-.015 + (.008)	-.091	-.022 * (.009)	-.102	-.030 * (.013)	-.102	-.030 * (.013)
Dummy: risk averse	.058	.015 (.009)	.031	.009 (.012)	.011	.004 (0.18)	.011	.004 (0.18)
Dummy: female	-.095	-.023 * (.009)	-.111	-.032 ** (.011)	-.124	-.043 ** (0.14)	-.123	-.042 ** (.014)
(Value class)²	.122	.002 *** (<.001)	.160	.003 *** (<.001)	.281	.007 *** (.001)	.331	.008 *** (.001)
Auction (#1-30)	-.042	<.001 * (<.001)	-.090	-.001 *** (<.001)	-.063	-.001 ** (<.001)	-.061	-.001** (<.001)
Overall arousal (θHR)	.050	.001 ** (<.001)	.046	.001 ** (<.001)	.044	.001 ** (<.001)	.042	.001** (<.001)
Dummy: winner					.067	.020 ** (.007)	.139	.042*** (.009)
(Value class)² × winner							-.119	-.003** (.001)
Constant		.036 *** (.010)		.061 *** (.014)		.069*** (.019)		.065*** (.019)
	N = 3067 R² = .039		N = 3067 R² = .063		N = 3067 R² = .148		N = 3067 R² = .150	

Notes: robust standard errors clustered by subject in parentheses.
Significance levels are based on two-tailed tests.
+ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Figure 7 displays the impact of outcome role and value class on average SCR.amp, which indicates that losing despite a high or very high valuation had the potential to evoke strong emotions. Specification (4) captures this relationship with the interaction between outcome role and value class, and a Wald test confirms that the increase in explanatory power from specification (3) was significant ($\chi^2(1)=8.135$, $p<.01$). The coefficient for the dummy winner was positive and significant (*b=.042, p<.001*) (i.e., at the lowest value class (coded as 0), winning caused stronger emotional responses than losing). The coefficient of the variable for value class was also positive and significant (*b=.008, p<.001*) (i.e., in case that an auction was not won, every increase in value class increased the emotional response significantly). The interaction term (winner × value class) was negative and significant (*b=-.003, p=.004*) (i.e., the just-mentioned increase was lower but still positive (*.008 + (-.003) = .005*) if the auction was won). This pattern is consistent across treatments. We discuss this point in more detail in Section 5.

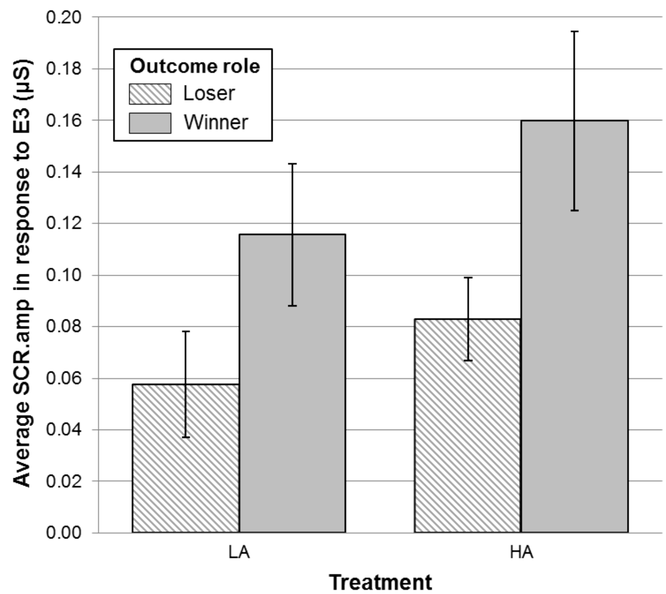

Figure 6. Average SCR.amp in Response to E3 for Different Outcome Roles and Treatments

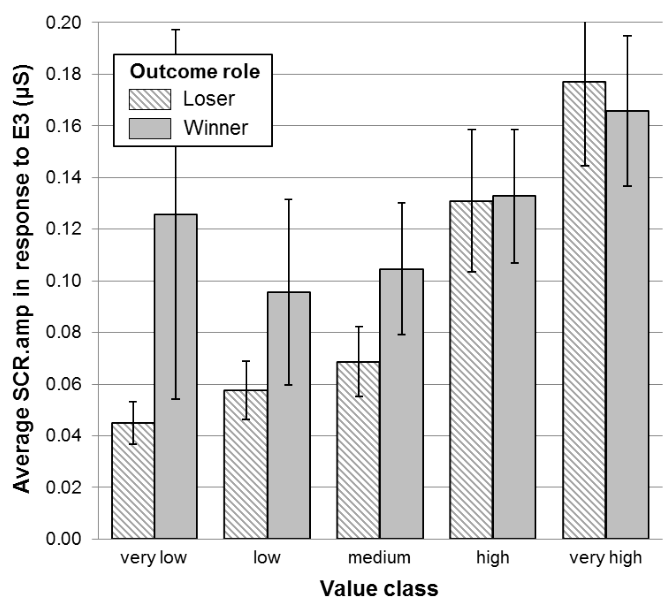

Figure 7. Average SCR.amp in Response E3 for Different Outcome Roles and Value Classes

4.2. Overall Arousal during Bidding (H2)

In this section, we consider θHR as a measure for the bidders' overall arousal levels before bid submission. When comparing the bidders' average θHR across all auctions on a subject level, we observed that arousal levels were marginally higher in the HA treatment than they were in the LA treatment (3.07% vs. 1.42%, one-tailed *t*-test, *t(101)=-1.635, p=.053*). While this result provides some support for H2, note that bidding behavior for low valuations is rather different than it is for high valuations (Engelbrecht-Wiggans & Katok, 2008; Kagel, 1995).

In particular, Engelbrecht-Wiggans and Katok (2008) established that, when participants think they do not have a realistic chance of winning an auction as is the case for low IPV, they behave aimlessly. It seems that bidders realize that their probability of winning the auction in these cases is small, and, therefore, they even place bids in excess of their own valuation to prevent another bidder from making a high profit (Kagel, 1995). This phenomenon can also be seen in the SCR.amp results reported in the last subsection, where immediate emotions were much less intense for low valuations. Therefore, in the following analysis, we use only auctions with IPV equal to or higher than 60 MU (i.e., the upper 50% of the IPV distribution), which means that, from the series of 30 auctions a subject participated in, we consider on average roughly 15 auctions in the analysis.

Correspondingly, Figure 8 depicts the bidders' average θHR across all auctions in which their IPV was equal to or higher than 60 MU. When comparing the bidders' θHR in those auctions, we can see that overall arousal levels were significantly higher in the HA treatment than in the LA treatment (3.92% vs. 1.79%, one-tailed *t*-test, $t(101)=-1.920$, $p=.029$). Thus, in line with hypothesis H2 and confirming the results on immediate emotions, participants were less aroused when they bidded against computer opponents.

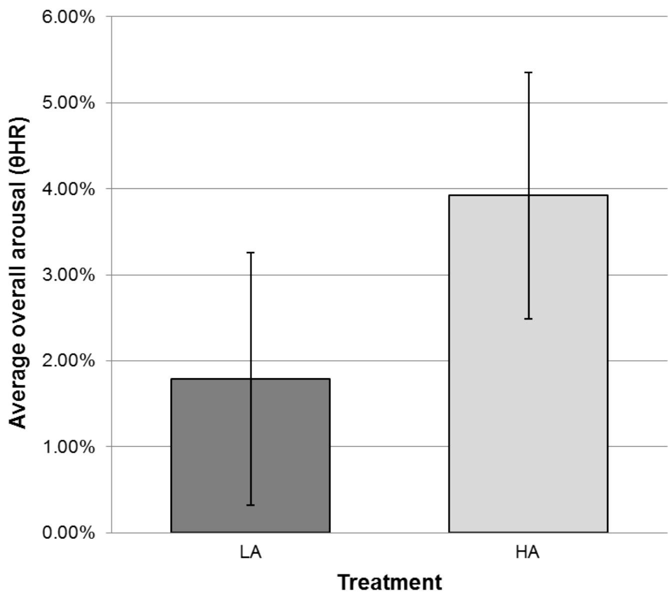

Figure 8. Average Overall Arousal (θHR)

4.3. The Relationship between Agency, Overall Arousal and Bidding (H3–H5)

Based on the literature, in Section 3, we hypothesize that there is a relationship between bidders' arousal and bidding behavior for high agency (H4) and that this relationship is mitigated for low agency (H5). To test this relationship, we first analyze the Pearson correlations between arousal and bids grouped by treatment[9]. The analysis reveals a statistically significant negative correlation between arousal and bids ($n=64$, $r=-.213$, $p=.046$, one-tailed) in the HA treatment but no significant correlation between arousal and bids in the LA treatment ($n=39$, $r=-.081$, $p=.313$, one-tailed).

The correlation analysis established a relationship between arousal and bidding behavior in human opponent markets in a simple setting. While compelling, the previous results may not hold up to more rigorous analysis. To control for other known effects on bidding behavior, we performed a mediation analysis based on our research model (cf. Figure 1) and test the conditional indirect effect. We conducted the analysis according to Krull and MacKinnon's (2001) mediation analysis approach. We conducted the GLS regressions summarized in Table 4 on the level of single auctions by using robust standard errors clustered by subject. The independent variables were treatment (LA: 1, HA: 0), sex (female: 1, male: 0), bidders' arousal (θHR), and whether or not subjects were classified as risk

[9] As we outline in Section 4.2, we based the analysis on auctions with IPV equal to or higher than 60 MU (i.e., the upper 50% of the IPV distribution).

averse (1: risk averse, 0: not risk averse) based on Holt and Laury's (2002) questionnaire. Additionally, we controlled for valuations and auction sequence.

Consistent with our previous analysis and, thus, providing further support for H3, specification (1) shows that arousal was also significantly lower in the computer opponents markets when controlling for auction sequence and valuation (*b=-2.304, p=.028*). In line with hypothesis H3, the results of specification (3) show that bidders placed lower bids in computer markets (*b=-3.101, p=.002*). Testing H4 and H5, we found that bidders placed lower bids when they were aroused (*b=-.110, p<.001*), while this effect was conditional on whether agency was high or low (*b=.111, p=.004*). Moreover, a Wald test confirmed that the increase in explanatory power from specification (2) to specification (3) was significant ($\chi^2(2)=20.706$, $p<.001$). Note that these results are robust against using different time frames (cf. Appendix A).

Table 4: GLS Regression Models for Overall Arousal and Bids

Independent variables	Dependent variables					
	(1) Arousal		(2) Bid		(3) Bid	
	Beta	Coeff.	Betta	Coeff.	Beta	Coeff.
Dummy: LA treatment	-.116	-2.304 * (1.049)	-.022	-.513 (.911)	-.134	-3.101 ** (.991)
Dummy: risk averse	-.093	-2.298 + (1.219)	.012	.336 (.966)	.004	.130 (.944)
Dummy: female	-.010	-.240 (1.344)	.087	2.361 * (1.022)	.089	2.414 * (.982)
Valuation	.067	.044 ** (.016)	.844	.649 *** (.016)	.844	.649 *** (.015)
Auction (#1-30)	-.152	-.168 *** (.030)	.006	.008 (.020)	-.004	-.005 (.019)
Overall arousal (θHR)					-.094	-.110 *** (.024)
LA treatment × overall arousal					.114	.111 ** (.039)
Constant		4.556 * (1.805)		16.515 *** (1.406)		19.440 *** (1.502)
	N = 1506 R^2 = .051		N = 1506 R^2 = .726		N = 1506 R^2 = .736	

Notes: robust standard errors clustered by subject in parentheses.
Significance levels are based on two-tailed tests.
$^+$ *p* < .10; * *p* < .05; ** *p* < .01; *** *p* < .001

Figure 9 illustrates the relationship between arousal and bids grouped by treatment. We see that, in the LA treatment, the average bid appeared to be completely invariant to arousal. The HA treatment differed markedly and exhibited decreases in average bid between low and high arousal. It appears as if the participants were not only more aroused when they were bidding against other humans but that their bidding behavior was correlated with arousal. This finding is also reflected in an interaction term between LA and arousal (*b=.111, p=.004*). To test the significance of this conditional indirect effect of arousal on bids, conditional for agency, we conducted a bootstrapping analysis. Based on 5,000 bootstrapped samples using bias-corrected 95 percent confidence intervals, the analysis revealed a significant indirect effect of arousal on bids for high agency (*IE=.447, SE=.072, LL=.307, UL=.589*). LL and UL refer to the lower and upper limit of the 95 percent confidence interval. The indirect effect was significantly different from zero at p<.05 (two-tailed). In contrast, the corresponding analysis for low agency reveals that the indirect effect was not significant (*IE=-.027, SE=.489, LL=-1.020, UL=.913*). Table 5 summarizes these results. Taken as a whole, our results support H3, H4, and H5. In the traditional context of markets with high agency, bidders were more aroused, and this arousal was also directly reflected in their bids. In markets with low agency, however, bidders were less aroused and the indirect effect of arousal on bids disappeared. In other words, low agency mitigated both arousal and the relationship between arousal and behavior. At this stage, it remains unclear whether the mediating role of arousal was due to a causal relationship of arousal on bids or because bidders who placed lower bids against other human bidders were also more aroused. We discuss this point in more detail in Section 5.

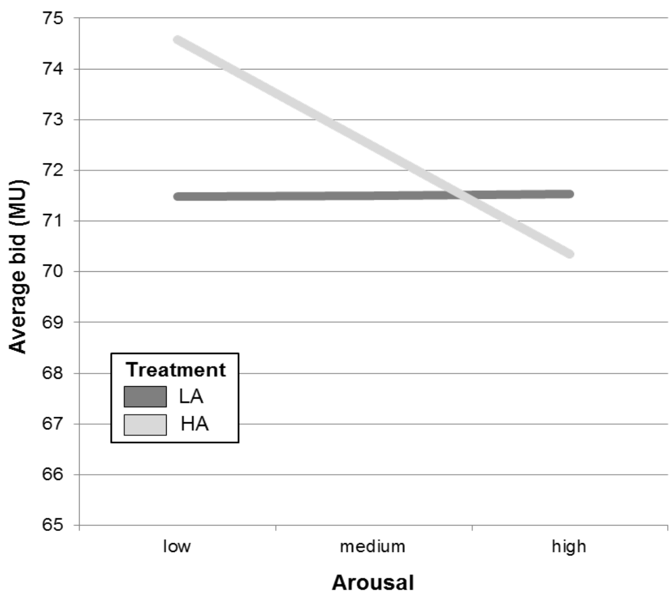

Figure 9. Relationship between Overall Arousal and Bids

Table 5. Indirect Effects for HA and LA Treatment

	Indirect effect	Boot SE	$LL_{95\%CI}$	$UL_{95\%CI}$
High agency	.447	.072	.307	.589
Low agency	-.027	.490	-1.020	.913

4.4. Allocation Efficiency

The results thus far focus on the bidders' immediate emotions, arousal, and bidding behavior. A question of overarching interest is that of outcome efficiency and the differences between markets with human and computerized agents. Following Vickrey (1961), we considered an auction to be efficient if the bidder with the highest IPV won the auction. In the case of a tie in terms of IPV, the auction was efficient if any of the highest IPV bidders won the auction. If bidders submitted the same, highest bid, the winner was determined randomly. In such cases, the auction was considered efficient, with a weight corresponding to the ex-ante chances of winning the auction for the bidder with the highest IPV. Table 6 summarizes the efficiency results for the HA and LA treatment.

Table 6. Allocation Efficiency for HA and LA Treatment

	# efficient	# total	Efficient	Not efficient
High agency	647.5	720	90%	10%
Low agency	427	480	89%	11%

Overall, roughly nine out of 10 of the auctions were efficient. Broken down by treatments, the results show only little difference. Auctions with high agency were efficient in 89 percent of the cases. Auctions with low agency were efficient in 90 percent of the cases. The difference is not significant at any conventional level (Chi-squared test, *p=.590*). It appears that, despite the fact that participants were more aroused overall in auctions with high agency, there was little impact on efficiency. Despite the lack of significance, this is the first evidence we are aware of that links competition with computer opponents, overall arousal, and auction efficiency. While a definitive answer fails to emerge and while we do not originally focus on efficiency, it is interesting enough to be addressed in follow-up research to study the differences in efficiency in human-only, computer-only, and mixed-market settings.

5. Discussion and Conclusions

5.1. Summary of Results

Most of the important markets in the world have become electronic. Computerized agents in these markets support humans and allow them to focus on other value-added tasks by alleviating the attention constraints involved in continuously monitoring market activity. The presence of computer agents affects the way humans perceive their environment, which the notion of *agency* captures. In recent years, and beyond cooperative and communicative interaction, computer agents have also become *competitors* to humans (e.g., in trading or auctions) (Brogaard et al., 2014; Hendershott et al., 2011). In this work, we analyzed the interplay of agency, affective processes, and bidding behavior in FPSB auctions in a controlled laboratory experiment in which subjects competed against either human participants (high agency) or computerized agents (low agency).

Our economic and physiological results indicate that the intensities of the bidders' immediate emotions in response to different auction events (e.g., submitting a bid) were weaker for low than for high agency (H1). Emotional intensity depended on the bidders' individual valuations and was particularly strong in response to winning an auction. Bidders' overall arousal levels were lower when bidding against computerized agents (H2). We found that, overall, bidders submitted lower bids in the low- than in the high-agency condition. Moreover, agency and overall arousal affected bidding in another, interactive way: while higher degrees of overall arousal were associated with lower bids for high agency (H4), this relationship was mostly mitigated in the low-agency treatment (H5). In other words, overall arousal indirectly affected bidding behavior, which was conditional on agency: computer opponents appeared to mitigate bidders' emotionality during the auction.

5.2. Managerial Implications

From the practical perspective of electronic auction platforms, our study has several implications. First, by letting auction participants interact with other humans rather than computer agents, an auction platform operator can foster social competition among the participants. Analogously, competing against computers has a mitigating effect on the affective processes and their impact on behavior. Depending on the context, platform operators can manipulate agency by emphasizing or concealing the participation of human peers (e.g., by providing social cues such as usernames and profile pictures). For consumer auction platforms where the thrill of beating competitors is a core element of the shopping experience and value proposition (Lee et al., 2009b), emphasizing the presence of other human bidders can be an important instrument to create a pleasurable shopping experience. Another relevant factor in this regard is gender. Prior studies have found virtual humans to be more persuasive when matching a subject's gender (Guadagno et al., 2007) and that female users exhibit stronger effects with regard to demographically similar recommendation agents in e-commerce shopping environments (Qiu & Benbasat, 2010). In our setting, subjects did not know their opponents' gender. Females, however, submitted higher bids and—similar to the results of Riedl et al. (2013) on stress reactions of computer users—exhibited lower intensities of immediate emotions in terms of SCR. We did not observe differences in overall arousal. This result may indicate females' less reward-driven nature compared to male bidders, which is reflected in both the former's higher bids and less-pronounced immediate emotions in response to auction events. We did not observe interaction effects between gender and the relationships investigated in our research model.

Second, besides the considerations regarding agency, the impact of platform design impact on immediate emotions and overall arousal is also an important aspect for attracting and retaining customers (Cronin, Brady, & Hult, 2000; Deng & Poole, 2010). In general, emotional experience plays an important role for Internet auction site sponsors because it distinguishes them from fixed-price competitors (Ariely & Simonson, 2003; Lee et al., 2009b). For bidders in consumer auctions, emotional experience can even be seen as a source of hedonic value (Childers, Carr, Peck, & Carson, 2001). Single design elements of websites can promote or mitigate affective processes in users, which, in turn, affect their behavior and general attitude towards the platform (Cronin et al., 2000; Deng & Poole, 2010). Menon and Kahn (2002, p. 39) argue that online marketers can use "very pleasing, enjoyable stimuli to encourage browsing and receptivity to impulse shopping". In this sense, one should design their platform to be experienced positively to create hedonic value for the customer. Auction format is one way to induce immediate emotions. When comparing our results with other studies, we can see that different auctions formats are associated with different emotional intensities. Adam et al. (2012) found that, in Dutch auctions, the frustration of losing was experienced relatively stronger than the respective joy of winning. In contrast, our results, in line with the results of Astor, Adam, Jerčić, Schaaff, and Weinhardt (2013), show that the joy of winning a FPSB auction was strong. By choosing a specific auction mechanism, auctioneers can, to some extent, control the set of immediate emotions a user experiences. By choosing a FPSB auction over a Dutch auction, for instance, the market operator might seek to promote the joy of winning and mitigate the experience of negative emotions. In addition to Astor et al. (2013), our results show that the bidders experience immediate emotions in response to other auction events (e.g., in response to submitting their bid) and even more so when interacting with human bidders. Ku (2008, p. 14) argues that, if bidding itself is arousing, it can "feed a vicious cycle of bidding and overbidding". Thus, in dynamic auctions, such emotions may eventually promote higher payoffs for the auctioneer. For instance, eBay practices such an approach by alerting bidders immediately via email when another bidder has outbidden them.

Third, agency and overall arousal are related to behavioral patterns that the auction platform operator can exploit. In particular, bidders seem to engage in socially competitive bidding in high-agency settings by trying not only to win the commodity at stake but also to beat their peers. This behavior leads to higher margins for the operator since bidders emotionally price in their anticipated joy of winning or frustration of losing. In addition to that, bidders in the high-agency setting submit lower bids when more aroused, which ultimately results in lower prices for auctions in which bidders with high arousal levels compete. Given a high-agency auction setting, marketers may want to manipulate the level of emotional behavior to inflate prices. For this purpose, the platform operator can increase or decrease the bidders' arousal by, for example, inducing time pressure, providing social cues for the existence of other human bidders (e.g., rankings, profile pictures), or confronting the bidders with thrilling wording and/or visual stimuli (e.g., IAPS, Gregor, Lin, Gedeon, Riaz, & Zhu, 2014; Lang, 1995).

On a more general level, our results give reason to believe that the dominance of algorithmic traders and high-frequency traders in financial markets does not only affect market efficiency and liquidity (Brogaard et al., 2014) per se but also has a direct effect on the human traders' affective processes and behavior. Regulatory authorities and the human traders and the organizations they represent should take this finding into account.

Finally, from the perspective of market participants, our results show that their behavior is related to their overall arousal. We found no reason to believe that market participants can benefit from an awareness and active consideration of this relationship. Since we measured arousal continuously and before bid submission, it may well be that providing market participants with real-time biofeedback helps them to re-evaluate their decisions (e.g., buy or sell orders, accept or reject an offer) before making irreversible decisions with undesired consequences for themselves and the organizations they represent. To this end, professional traders and investors have started using serious games with biofeedback to train their emotion-regulation capabilities (Astor et al., 2014; Fenton-O'Creevy et al., 2012). In this sense, IS design science and human-computer interaction research can provide the methods and tools that help market participants to monitor, track, and regulate their emotions during bidding to make better decisions (vom Brocke et al., 2013).

5.3. Theoretical Implications

This study disentangles competitive arousal and bidding behavior in auctions with different levels of agency (i.e., with either human or computerized opponents). Briefly, bidders experience less arousal overall and systematically bid lower when facing computer opponents. Theoretically, this finding suggests that human behavior is less driven by emotional factors in low-agency settings, which is consistent with previous results on bargaining (Ben-Shakhar, Bornstein, Hopfensitz, & van Winden, 2007; van't Wout et al., 2006). Arousal and its link to bids are more pronounced when bidding against human opponents. In accordance with the literature, we relate this finding to the socially competitive nature of auctions (Adam, Krämer, Jähnig, Seifert, & Weinhardt, 2011; Ku et al., 2005) (i.e., bidders strive to win a social competition against their peers rather than to merely gain a material surplus). Everything else equal, higher arousal is associated with lower bids. Our study demonstrates that this finding only holds for the high-agency treatment. Thus, as we outline in our research model, the factors agency and arousal interact, where low agency mitigates arousal per se and the relationship between arousal and bidding behavior. Moreover, bidding behavior is on average nearly identical for both treatments when arousal is not controlled for, which also explains the fact that efficiency is not significantly impacted in our setting.

Our analysis shows that the intensities of individuals' immediate emotions in response to the auction outcome and to other events during the auction process are consistently stronger in the high-agency environment. The picture is more complex, however, with respect to the impact of the IPV. In general, the joy of winning an auction seems to be stronger than the frustration of losing for most IPV classes but is reversed for the highest-value classes. This finding provides support for the theories based on "equating the reference point with expectations rather than the status quo" (Köszegi & Rabin, 2006, p. 1135). We suggest that, based on their individual IPV, the bidders form expectations about the auction outcome. Winning an auction with a low valuation is unlikely and, thus, surprisingly positive. Similarly, the frustration of losing is undoubtedly stronger if one's own IPV and, thus, the chances of winning are comparatively high ex ante. Our results confirm this notion. We found that the frustration of *not winning* even exceeds the joy of winning for the higher value class slightly. In our regression analysis, we accounted for this effect by using the interaction term *value class* $\times$ *dummy winner* (see Table 3). The effect was significant and negative, which reflects the stronger impact of losing a high IPV auction. In this regard, our results are contrary to the assumptions of previous research to some extent. In the context of common value auctions, van den Bos et al. (2008, p. 488) argue that "winning and losing affect utility independent of the monetary consequences of an auction". Our results show, however, that higher nominal payoffs yield stronger immediate emotions. In particular for the highest values, the frustration of losing can be stronger than the joy of winning, whereas the latter is usually assumed to be the dominating emotion. With regard to agency, we found that high agency yields stronger immediate emotions than low agency, and—consistently in both treatments—winning yields stronger emotional responses than losing. Interestingly, *winning* against computer opponents, however, causes stronger responses than *losing* against human opponents. On the one hand, we can see this finding as an indication that the joy associated with the monetary reward of winning an auction (low-agency treatment) outweighs the frustration of losing the inherent social competition of auctions (high-agency treatment). On the other hand, however, we can also see it as an indication that not only does the joy of winning an auction in the low-agency treatment stem from the monetary reward but also that bidders, in fact, also derive joy from beating a computer opponent even though to a lower extent than they do for human opponents. This finding is in line with the reasoning of Nass and Moon (2000) that computers can take on the role of social actors.

Moreover, the emotions in response to submitting a bid and waiting for the auction outcome are experienced more intensely in auctions with human opponents and are positively correlated with the individual IPV. At both events, however, the bidder does not receive new information. Theoretically, this finding implies that, in those moments, the bidders experience immediate emotions in response to *thinking* about past or future events (Bechara & Damasio, 2005). The immediate emotion in response to placing a bid may, for instance, stem from experiencing a fear of losing or, putting it in a positive way, from a desire to win the auction, which is more intense for high IPVs. In any case, our results show that the bidders already experience emotions during the auction process even though their information set is not updated in the sense of auction theory (Krishna, 2002). This finding provides a physiological indication for the existence and the intensities of these emotions and, thus, yields further insight into the underlying affective processes of humans interacting with electronic auction websites and other information systems. Our results show that even seemingly irrelevant information events can trigger affective processes in users. Such processes may have important ramifications for website and interaction-process design, perception, and success (Cronin et al., 2000; Deng & Poole, 2010).

5.4. Limitations and Future Research

This study has several limitations. First and most importantly, our experiment focused on FPSB auctions, which left “no opportunity for competitive fire to escalate with the progression of the auction” (van den Bos et al., 2008, p. 484). Our results show that differences in immediate emotions and overall arousal already exist in a static, almost clinical environment in which bidders are isolated from each other by using dividing blinds and earmuffs and only interact very indirectly by exchanging sealed bids. Thus, we need to further investigate and contrast the differences in affective processes and bidding behavior in more dynamic auctions (e.g., Japanese, Dutch, or Dollar auctions) (Adam et al., 2011; Ku et al., 2005). Moreover, the bidders submitted single bids in FPSB auctions. Future research may, therefore, also take affective processes in response to repeated bidding in the same auction into account to address effects of pseudo-endowment (Ariely & Simonson, 2003) and bidders’ attachment (Köszegi & Rabin, 2006). Finally, with the increasing share of automated trading in stock market activity in general, comparing the results of our study with market decision making in continuous double auctions could yield promising findings for financial markets.

Second, our study does not consider graphical representations of the bidders, which certainly is an important factor for the role of agency in competitive human-agent interaction (Benbasat, Dimoka, Pavlou, & Qiu, 2010; Davis, Murphy, Owens, Khazanchi, & IIze, 2009; Fox et al., forthcoming; Nunamaker, Derrick, Elkins, Burgoon, & Patton, 2011; Riedl, Mohr, Kenning, & Davis, 2011; Riedl et al., 2014b). In this regard, several prior studies explicitly disentangle the influence of agency and graphical representations with important implications for emotions and behavior in the context of cooperative and communicative tasks in virtual environments (Appel et al., 2012; Guadagno et al., 2007; Nowak & Biocca, 2003; von der Pütten et al., 2010). In our study, we deliberately decided to not use graphical representations since, in electronic auctions, the bidders usually remain anonymous and do not see photos or avatars representing the other bidders (Steinhart et al., 2013)[10]. However, beyond the role of recommender agents that provide consumers with advice on products (Benbasat et al., 2010), some entertainment shopping platforms have actually begun to use avatars or other forms of graphical representations (e.g., dealdash.com) to boost social competition. Therefore, varying the appearance of the human bidders (and also the computerized agents) in a controlled and traceable way seems promising to disentangle the effects related to agency from those related to social cues (e.g., by displaying actual photos or stylized representations). To approach the inherently interwoven influences of representation and agency, two approaches come to mind (von der Pütten et al., 2010). The threshold model of social influence (Blascovich et al., 2002) states that social verification is achieved (and, hence, social reactions are triggered) if either the users’ perception of agency is high or low agency is compensated by higher behavioral realism. The ethopoeia concept (Nass & Moon, 2000), in contrast, denies agency as a relevant factor outright and holds that social reactions are evoked if only there are sufficient social cues, such as natural speech, interactivity, or the filling of social roles. We acknowledge that further investigating the interplay of agency and graphical representations is due. Despite the high importance of graphical representations with respect to the effects of agency, our results indicate that, even without social cues, agency proves to be a critical factor, which we find to be reflected in more intense immediate emotions and arousal (H1, H2), higher bids (H3), and a stronger relation between arousal and bidding behavior (H4, H5).

[10] The perceptible digital representation of a computational algorithm is usually referred to as agent, while the perceptible digital representation of a human is referred to as avatar (Bailenson & Blascovich, 2004).

A third limitation is that, although our analysis reveals a mediating role of overall arousal, we cannot draw a reliable conclusion about causality from arousal to bids. Even though we measured arousal in the time frame six to three seconds *before* the bid was submitted, it might well be that subjects *intended* to submit a particularly low bid and then—because of the thrilling thought about the potential gains—became more aroused, and eventually submitted their bid according to their initial plan. It is striking though that the relationship between arousal and bids disappeared when the bidders face computer opponents. To further disentangle this effect, future research may induce different levels of arousal independent of the auction process, which may be achieved, for instance, by letting subjects play an arousing game, listen to arousing music, or experience stress prior to engaging in the auctions (Riedl, Kindermann, Auinger, & Javor, 2012; Riedl et al., 2013).

A fourth limitation is that our analysis of overall arousal and immediate emotions is limited to HR and SCR measurements. Taking into account respiration would potentially increase the explanatory power of our analysis and capture further important aspects (Laude, Weise, Girard, & Elghozi, 1995). Due to the nature of our experiment that required the presence of at least three participants in the laboratory at the same time, we were limited in the amount of physiological parameters and, therefore, focused particularly on HR and SCR. Moreover, and complementary to the analysis of objective physiological parameters, it would be interesting to additionally collect subjective data based on ex post interviews (Gallagher et al., 2002) or surveys (Ortiz de Guinea et al., 2013) to shed more light on (1) the bidders' cognitive processes (e.g., cognitive load, strategies, and motives) and (2) the bidders' perceived valence of overall arousal and immediate emotions. By combining subjective and objective measures, future research can disentangle the influence of agency on bidders' cognitive and affective processes and determine to what extent these processes are conscious or unconscious in nature (Fox et al., forthcoming). Providing strong evidence for the importance of unconscious processes in the context of agency, Fox et al. (forthcoming, p. 25) found in a meta-analysis of 32 studies that "objective measures revealed greater differences for agency than subjective measures". Thus, using electroencephalography as an objective measure of cognitive load and valence (Gregor et al., 2014; Ortiz de Guinea et al., 2013) seems to be a promising complementary approach in this context.

5.5. Conclusions

Taken as a whole, our study shows that the intensity of bidders' immediate emotions and overall arousal and the relationship between arousal and bidding behavior is mitigated if agency is low (i.e., when bidding against computerized agents rather than human opponents). Both electronic market platform operators and bidders should be aware of this relationship and consider it during market design and when competing against other bidders—human or not. Given that some of the world's most important markets contain both human and computerized agents, understanding the impact of agency on bidding behavior and overall market parameters is not only of academic but also of industrial, regulatory, and societal interest. With respect to technological progress, we have reason to believe that interaction between humans and computerized agents will become increasingly important in business processes and also in daily life. We believe that neuroIS research can contribute to a better understanding of the underlying affective processes and, thereby, support the decision making process.

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Appendix

Appendix A: Supplementary Material

Different Windows Sizes for Arousal Computation

In the analysis, we used the time window of six to three seconds *before* submitting a bid for computing overall arousal (i.e., a time window of three seconds and a buffer of three seconds (3+3)). In the following analysis, we test the robustness of our results by using different window sizes for computing arousal. Table A-1 and Table A-2 summarize a set of GLS regression models for arousal and bids with different window size for arousal. The results are consistent across the different windows sizes.

Table A-1. GLS Regression Models for Overall Arousal with Different Window Sizes

Independent variables	Overall arousal (window size for overall arousal)				
	(1+5)	(2+4)	(3+3)	(4+2)	(5+1)
Dummy: LA treatment	-2.257 * (0.974)	-2.237 * (1.012)	-2.304 * (1.049)	-2.262 * (1.055)	-2.170 * (1.048)
Dummy: risk averse	-2.216 + (1.146)	-2.210 + (1.192)	-2.298 + (1.219)	-2.405 * (1.222)	-2.430 * (1.217)
Dummy: female	-.228 (1.339)	-.246 (1.312)	-.240 (1.344)	-.129 (1.348)	-.087 (1.338)
Valuation	.039 * (.018)	.042 * (.017)	.044 ** (.016)	.045 ** (.016)	.046 ** (.015)
Auction (#1-30)	-.174 *** (.033)	-.175 *** (.031)	-.168 *** (.030)	-.158 *** (.029)	-.151 *** (.028)
Constant	5.045 ** (1.915)	4.815 ** (1.847)	4.556 * (1.805)	4.298 * (1.758)	3.899 * (1.736)
	N = 1506 R^2 = .047	N = 1506 R^2 = .049	N = 1506 R^2 = .051	N = 1506 R^2 = .052	N = 1506 R^2 = .054

Notes: robust standard errors clustered by subject in parentheses.
Significance levels are based on two-tailed tests.
$^{+}$ p < .10; * p < .05; ** p < .01; *** p < .001

Table A-2. GLS Regression Models for Bids with Different Window Sizes for Overall Arousal

Independent variables	Bid (window size for overall arousal)				
	(1 + 5)	**(2 + 4)**	**(3 + 3)**	**(4 + 2)**	**(5 + 1)**
Dummy: LA treatment	-2.656 ** (.929)	-2.800 ** (.960)	-3.101 ** (.991)	-3.120 ** (1.001)	-3.035 ** (1.005)
Dummy: risk averse	.165 (.944)	.149 (.945)	.130 (.944)	.110 (.945)	.085 (.945)
Dummy: female	2.411 * (.984)	2.408 * (.984)	2.414 * (.982)	2.414 * (.982)	2.406 * (.982)
Valuation	.648 *** (.015)	.649 *** (.015)	.649 *** (.015)	.649 *** (.015)	.650 *** (.015)
Auction (#1-30)	-.003 (.019)	-.004 (.019)	-.005 (.019)	-.006 (.019)	-.007 (.019)
Overall arousal (θHR)	-.090 *** (.021)	-.099 *** (.022)	-.110 *** (.024)	-.120 *** (.027)	-.130 *** (.030)
LA treatment × overall arousal	.089 ** (.032)	.096 ** (.035)	.111 ** (.039)	.116 ** (.042)	.116 * (.046)
Constant	19.04 *** (1.491)	19.21 *** (1.492)	19.44 *** (1.502)	19.58 *** (1.518)	19.67 *** (1.534)
	N = 1506 R^2 = .734	N = 1506 R^2 = .735	N = 1506 R^2 = .736	N = 1506 R^2 = .736	N = 1506 R^2 = .737

Notes: robust standard errors clustered by subject in parentheses.
Significance levels are based on two-tailed tests.
$^+$ p < .10; * p < .05; ** p < .01; *** p < .001

Appendix B: Participants Instructions

[We include on the following pages English translations of the instructions. Please note that the instructions are only translations for information; they are not intended for publication or to be used in the lab. The instructions in the original language were carefully polished in grammar, style, comprehensibility, and avoidance of strategic guidance.]

You are about to participate in an experiment of economic decision making. During the experiment, your skin conductance, pulse, and heart rate are recorded. You can earn **real money** in this experiment. How much money you earn depends on both your decisions and the decisions of the other participants in this room [the computerized bidding agents]. The experiment consists of **30 consecutive auctions**. The experimental software manages a cash account for you that balances gains and losses out of the 30 auctions. A positive cash balance is paid to you at the end of the experiment, a negative one is claimed. During the experiment gains and losses are calculated in monetary units (MU). 16 MU equal a real amount of 1 Euro (EUR). 1 MU therefore equals 6.25 Cents. Communication between participants is not allowed.

Design of an Auction

In each auction you bid for a fictitious asset. Information about your personal resale value of the asset is given to you prior to an auction. This value is known only to you. Within each auction you and two other participants [computerized bidding agents] compete in an auction. [The computerized bidding agents follow a strategy that you do not know.] The two other bidders also receive their personal resale value prior to the auction and it is known only to them.

As soon as the auction starts you have the possibility to place your bid via a **number pad**. If you make a mistake you can correct your bid through clicking on the "**Correct**" button. It deletes the last digit you entered. You finally place your bid by clicking on "**Submit bid**" (cf. Figure B-1). [The computerized bidding agents bid simultaneously and do not know about other bids.]

Figure B-1. Number Pad, Correction, and Bid Placement

If all bidders made their bid, the one with the highest bid is determined. This bidder wins the auction and pays the price he or she bid for the asset. If two or more bidders place the same highest bid, the experimental software selects one of them by equal chances. If you are not the highest bidder you receive a payoff of zero. If you are the highest bidder your payoff is calculated in the following way:

Payoff = Personal Resale Value – Price

The Personal Resale Value

Prior to every auction you and the other participants [computerized bidding agents] receive information about their personal resale value but not about the resale value of the others. In each auction you exactly know how high your personal resale value is in the particular auction.

The personal resale value is drawn **independently** out of the integer values between **11** and **110** for each bidder. Every value is equally likely to be chosen. This corresponds to an urn with 100 balls which are labeled with numbers from 11 to 110. A random draw from the urn determines the resale value of the bidder's asset. After the draw the ball is put back into the urn and the resale value for the next bidder is drawn.

The winner of an auction obtains her personal resale value minus her bid. This connection should be explained through an example. Assume that you have a **personal resale value of 65 MU** and you have been the bidder with the highest bid. Then there are the following cases:

1. Your bid lies **above** your resale value, e.g. 67 MU

   ➔ Loss of 65MU – 67MU = -2MU

2. Your bid **equals** your resale value, i.e. 65 MU

   ➔ Zero payoff: 65MU – 65MU = 0MU

3. Your bid lies **below** your resale value, e.g. 61 MU

   ➔ Gain of 65MU – 61MU = 4MU

If one of the other participants (computerized bidding agents) is the highest bidder, the auction ends and you receive a payoff of zero.

Course of the Experiment

After the instruction phase there are five practice periods with five auctions to gain a better understanding of the experiment. Gains and losses out of these practice periods are not considered for the later payoff. After the practice periods there is a **five-minute** resting period where a fixation cross appears on the computer screen. The resting period is essential for the physiological measurement and later data analysis. Stay calm during this phase and try to move as little as possible.

The main course of the experiment consists of 30 consecutive periods where each of the six participants plays against two other participants (computerized bidding agents). In every period you and the other participants [computerized bidding agents] of your group participate in **one** auction as described above. After every period you are randomly re-matched to a new group of three bidders. Thus, you will play against frequently changing participants [computerized bidding agents]. The result of one auction does not affect following auctions. [Please note that the other five participants in this room do not have any influence on your auction outcome including gains and losses. Six participants are present because this laboratory has six places.]

Payment

At the end of the 30 periods a positive cash balance is paid to you and a negative one is claimed. The cash balance in MU is multiplied with a factor of 1/16 to get the payoff in Euro. I.e. if you have a cash balance of 400 MU you obtain a payment of 25 EUR. 1 MU equals 6.25 Cents.

... and finally, some comments

If you have any questions regarding the experiment, please remain seated, raise your hand and wait until the experimenter approaches you. Then, ask your question as quiet as possible. Utilize only your free hand to interact with the experiment system. The hand linked to the physiological measurement system must remain as calm as possible during the whole experiment. Try to avoid every movement as this can distort the measurement. Upon the end of the experiment, remain seated and wait until the experimenter has removed the electrodes from your arm and wrist. The participant instructions remain at your place.

Before the experiment starts you are going to answer some questions of general understanding about the rules of the experiment on your computer screen. Then, five practice periods are performed as described above. Gains and losses are not considered here. Then the five-minute resting period starts and therewith the actual experiment.

Important note: Please click your mouse as quiet as possible and with little effort. You will now be equipped with earmuffs to reduce the influence of background noise.

Appendix C: List of Acronyms

ANS	autonomic nervous system
E1	auction event 1 (bid submit)
E2	auction event 2 (waiting for results)
E3	auction event 3 (winner information)
ECG	electrocardiogram
EDA	electrodermal activity
FPSB	first-price sealed-bid
HA	high agency
IAPS	international affective picture system
IE	indirect effect
IPV	independent private value
LA	low agency
$LL_{95\%CI}$	lower limit of the 95% confidence interval
µS	microsiemens
SCL	skin conductance level
SCR	skin conductance response
SCR.amp	skin conductance response amplitude
$UL_{95\%CI}$	upper limit of the 95% confidence interval

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