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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 mitigate the intensity of bidders' immediate emotions in response to discrete auction events, such as submitting a bid and winning or losing an auction, as well as the bidders' overall arousal levels during the auction. Moreover, bidding behavior and its relation to overall arousal are affected by agency: whereas overall arousal and bids are negatively correlated when competing against human bidders, this relationship is not observable 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

1 | Introduction

Information technology has revolutionized markets. While traditionally, a market was 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 to 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 et al., 2005). In modern financial markets, the chances are greater to trade with an algorithm than with a human being (Brogaard et al., 2014). Demonstrating the importance of computerized traders, Hendershott and colleagues showed that algorithmic traders were responsible for a large increase in liquidity available on the New York Stock Exchange (Hendershott et al., 2011). Taken as a whole, computerized traders presumably are responsible for over 70% of the volume in US stock markets (Brownlees et al., 2011). A subset of computerized traders, called high frequency traders (HFT), make up more than 40% of the trading volume on Nasdaq and were 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 the human traders' affective processes and behav-

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ior as well as 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, it is safe to say that some participants are unhappy about the situation.[1] This leads to the question 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 conduct a NeuroIS laboratory experiment in which participants bid against other human participants in one treatment (high agency), and against computerized bidding agents in the other treatment (low agency). The level of agency is the only meaningful difference between treatments. Applying NeuroIS methods is particularly insightful in this study, as they allow us to measure proxies for market participants' affective processes which may partially be unconscious in nature. Moreover, NeuroIS enables us to assess this data at different stages of the auction process without having to interrupt the participants during decision making (Riedl et al., 2014; vom Brocke and Liang, 2014). In particular, we measure participants' heart rates (HR) and skin conductance responses (SCR) as proxies for their overall arousal and their immediate emotions. These measures are combined 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, i.e. high agency and low agency), we seek to better understand recent developments in electronic markets, and take a step towards explaining the impact of emotions.

Our results show that participants are significantly more aroused in the high agency treatment (human opponents) than in the low agency treatment (computer opponents). Moreover, participants submit lower bids when they experience higher levels of overall arousal. What is striking is that the relationship between overall arousal and bidding behavior is only present in the high agency condition. In the low agency condition, in contrast, bids and overall arousal levels are lower–and uncorrelated. Additionally, we observe participants' immediate emotions in response to auction events. Again, we find 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).

The remainder of this article is organized as follows. In the following section, we outline the theoretical background and hypotheses of our study. The next section then outlines the experimental design. In the results section, we analyze the bidders' immediate emotions in response to discrete auction events, as well as the interplay of agency, overall arousal, bidding behavior, and market efficiency. Finally, we discuss the theoretical and managerial implications of the study and present our conclusions.

2 | Theoretical Background and Hypotheses

Over the past decade, the presence of computerized agents has become pervasive in everyday live (Fox et al., in press). Where traditionally humans directly interacted with other humans, today many users interact with computerized agents. The domain of cooperative and competitive interactions has thus 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 defined as the extent to which a user believes that he or she is "interacting with another sentient human being" (Guadagno et al., 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. In the following, we therefore aim to 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 the user's affective processes and behavior, which in turn depends, among other factors, on the type of the task and the computer agents' behavioral realism (Blascovich et al., 2002; Fox et al., 2014; Guadagno et al., 2007; Lim and Reeves, 2010).[2] In particular, while it was found that agency has an influence in the domain of communicative tasks (e.g., persuasive communication (Guadagno et al., 2007, 2011), self-introduction (Nowak and Biocca, 2003; von der Pütten et al., 2010) and chatting (Appel et al., 2012) and cooperative tasks (e.g., trading items (Lim and Reeves, 2010), bargaining (Sanfey et al., 2003), and trust games (Riedl et al., 2014)), this influence seems to be even more pronounced in competitive tasks (Gallagher et al., 2002; Lim and Reeves, 2010; Polosan et al., 2011; Williams and Clippinger, 2002). In the

[1] See: "High-Speed Traders Race To Fend Off Regulators," Wall Street Journal, December 28th, 2012.

[2] In the literature, the investigation of agency often also considers the influence of the counterpart's graphical representation (e.g., Nowak and Biocca (2003); Appel et al. (2012); Riedl et al. (2014); Fox et al. (2014)). As though one of the features of online auctions is that the parties "remain anonymous and transactions between parties are of an impersonal nature" (Steinhart et al., 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 the Limitations and Future Research section

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.

As auctions are characterized by an inherent "social competition" (Delgado et al., 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 his or her bid (Engelbrecht-Wiggans and 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 (i) bidding in an electronic auction also involves affective processes (i.e., experiencing intense immediate emotions such as the joy of winning and the frustration of losing (Astor et al., 2013; Delgado et al., 2008; Ding et al., 2005), and competitive arousal (Ariely and Simonson, 2003; Ku et al., 2005), and that (ii) these processes are influenced by agency. With respect to affective processes, we are particularly interested in the bidders' immediate emotions, i.e., short-lived subjective experiences (Rick and Loewenstein, 2008) in response to specific auction events (Astor et al., 2013), as well as in the bidders' overall arousal, i.e., the intensity of the overall emotional state, during the auction process (Ku et al., 2005).[3]

We thereby build on the advances in NeuroIS (Dimoka et al., 2011; Riedl et al., 2010, 2014; vom Brocke and Liang, 2014; vom Brocke et al., 2013), 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 the affective processes of users interacting with information systems. In particular, SCR measurements have recently been used to investigate immediate stress reactions of computer users (Riedl et al., 2013) and HR measurements have been used to investigate users' overall arousal in the context of IS use patterns (Ortiz de Guinea and Webster, 2013) and enterprise resource planning systems (Ortiz de Guinea and Webster, 2013).

In summary, we investigate the interplay of agency, the bidders' affective processes, and bidding behavior in an integrated approach. Our research model is depicted in Figure 1. The underlying theoretical concepts and hypotheses are outlined in detail in the following subsections. Related literature, specifically concerning experimental studies on the impact of agency on human affective processes and behavior, is summarized and structured in Table 1 at the end of this section.

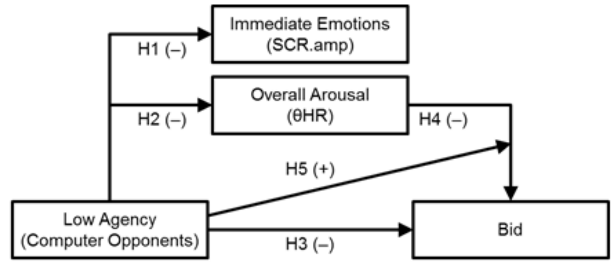

Figure 1: *Research Model*

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 et al., 2004; Loch et al., 2006). To succeed in social interactions, humans have developed a wide range of strategies, building both on cognitive (e.g., analytical and logical reasoning, perspective taking) and affective processes (e.g., immediate emotions, overall arousal). As 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). In order to assess and predict the intentions, beliefs, and behaviors of others, humans make inferences about their counterparts' mental states; a core human ability commonly referred to as "mentalizing" (Decety et al., 2004; Frith and Frith, 2006) or "Theory of Mind" (Polosan et al., 2011).

Mentalizing is defined as the "ability to read the mental states of other agents" (Frith and 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 and 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, it is important to highlight that mentalizing also includes affective processes (Frith and Frith, 2006; Lim and Reeves, 2010; Polosan et al., 2011). In particular, humans seek to simulate and reenact their counterparts' emotions through the brain's mirror system in order

[3]The term arousal can be used for describing both the intensity of immediate emotions (phasic arousal) and the intensity of the overall emotional state (overall arousal). In order to avoid such ambiguity, in this paper we use the term arousal only to refer to overall arousal.

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 and Frith (2006, p. 531)). In an electronic auction, for instance, bidders might try to assess their competitors' affective processes in order to predict their bids. Even though computer agents can be designed to simulate affective processes and take on the role of "social actors" (Nass and Moon, 2000; Zadro et al., 2004, p. 84), it must be expected that attempting to reenact the affective processes of computer agents is less pronounced than simulating and reenacting those of human counterparts (Lim and Reeves, 2010; Polosan et al., 2011). Affective processes are thus expected to be weaker when agency is low.

In addition to assessing emotions of others, 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 and Damasio, 2005). They are thus 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 those of others (Festinger, 1954). Such social comparisons can fuel overall arousal (Buunk et al., 1990; Lim and Reeves, 2010) and trigger immediate emotions, such as envy and gloating, which serve to keep track of "social status" (Bault et al., 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, his/her presence introduced a social reference point which 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 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 and 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 and Katok, 2008). Following social comparison theory, overall arousal and the intensity of immediate emotions should thus be lower when humans interact with computer agents.

This line of argumentation is well supported by empirical evidence. Sanfey et al. (2003) and Rilling et al. (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 et al. (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 et al., 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 and Reeves, 2010; Weibel et al., 2008), i.e. 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 and Bazerman, 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 and Bazerman, 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).[4] 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 worked out based on mentalizing and social comparison theory, however, competing with computer agents yields important differences to competing with humans. We thus 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. Research hypotheses H1 and H2 state:

Hypothesis 1. *The intensity of bidders' immediate emo-*

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

tions is lower in FPSB auctions with low agency than in FPSB auctions with high agency.

Hypothesis 2. *The level of bidders' overall arousal is lower in FPSB auctions with low agency than in FPSB auctions with high agency.*

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 et al., 2003), or causing different evasive actions when being approached by a virtual character (Bailenson et al., 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.[5] 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 take into account 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 and Schmidt, 1999).

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 and Fang, 2008). This eventually causes auction participants to overbid and pay more for an item than it is actually worth to them (Malhotra and Bazerman, 2008). In this sense, high agency causes market interaction to be seen as a "play-to-win game" (Stafford and Stern, 2002, p. 44)[6] in which "people enjoy winning–especially against their rivals–even at a price" (Malhotra and Bazerman, 2008, p. 80). Due to this characteristic of auctions, "the thrill of bidding, the excitement of winning, and the stimulation of beating competitors" have even been identified as reasons for the popularity of auctions (Lee et al., 2009, p. 77). Hence, the source of additional utility or disutility is attributed to the inherent social competition of auctions (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% 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, bidders are expected to place lower bids in such settings. For the case of common value auctions, for instance, Van den Bos et al. (2008) found a positive effect of agency 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 et al. (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. 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, bidders are expected to place lower bids in such settings. For the case of common value auctions, for instance, Van den Bos et al. (2008) found a positive effect of agency 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 et al. (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.

Associated with its effect on affective processes, we thus expect agency 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. Hypothesis 3 thus states:

Hypothesis 3. *In FPSB auctions with low agency, bidders*

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

[6]Correspondingly, in 2007 eBay launched an advertisement campaign called "shop victoriously," stressing 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, suggesting to hit back with an even higher bid.

place lower bids than they do in FPSB auctions with high agency.

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 established that both affective and cognitive processes have a definite influence on human decision making (Bechara and Damasio, 2005). Depending on the situation, however, the influence of either affective or cognitive processes on behavior can be more pronounced (Ariely et al., 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 et al., 2009; 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., 2009, 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., 2009). In the following we outline the theoretical basis for the moderating effect of agency on the relation of overall arousal and bidding behavior. We argue that–as affective processes are expected to be less intense in low agency auctions–there is reason to believe that also the relationship between overall arousal and bidding behavior is weaker when agency is low. We start off from traditional settings with human counterparts and, thus, high agency.

High Agency For such settings, it is commonly recognized 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 et al. (2007) argued that humans seem to follow an "affect heuristic," which 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 found that the relationship between arousal and decision making is twofold. On the one hand, situations involving risk are known to trigger arousal, as they can have material consequences for the decision maker (Trimpop, 1994). On the other hand, however, arousal can also cause an increased willingness to take such risks in order to achieve higher rewards (Ariely et al., 2006; Rivers et al., 2008). The perspective of evolutionary psychology provides a rationale for this, as "most appetitive systems in the brain, including hunger and thirst, are designed to increase motivation during times of opportunity" (Ariely et al., 2006, p. 88). This suggests a negative relationship between arousal and bids, as arousal enhances the motivational effects of rewards (Rivers et al., 2008). Higher rewards (or the chance on higher rewards, respectively) can usually only be realized by either higher levels of effort–or by taking more risk. 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. Increasing the potential profit (value of the good minus price paid) in a FPSB auction can only be realized by submitting lower bids, which concurrently entails a lower probability of winning the auction (Vickrey, 1961).[7] Lower bids may thus actually be caused by higher levels of arousal.

The above reasoning thus 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 the desire to win in a two-step process (Ku et al., 2005; Malhotra and Bazerman, 2008). First, factors like rivalry, time pressure, or social facilitation induce higher overall arousal levels. This higher arousal then fosters the desire to win against the opponent, superseding the original goal (for instance, generating the highest possible expected profit), and by this means affecting 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.

There is, however, ample evidence for the prior line of thought, stressing the enhancing power of arousal on the motivational effects of rewards. The empirical observations thus speak in favor of a negative relationship between arousal and bid height (Ariely et al., 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 et al. (2006) showed that (sexual) arousal is capable of increasing the subjective willingness to engage in unsafe ventures.

Taken as a whole, the theoretical perspective on arousal and bidding thus suggests a negative relation between arousal and bids for high agency scenarios. We therefore hypothesize that higher levels of arousal are associated with lower bids in

[7] 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, there is also a 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.

FPSB auctions. H4 states:

Hypothesis 4. *In FPSB auctions with high agency, higher overall arousal levels are related to lower bids.*

Low Agency While the tense atmosphere of socially competing with humans establishes a context that possibly pronounces the role of affective processes (cf. H1, H2, and H4), there is reason to believe that the working principles of linking arousal and bidding behavior are different for low agency. First, as bidders' affective processes are expected 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 and West, 2000). As we have outlined above, arousal is often attributed directly to the social competition of auctions. 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 unfair offers by humans were rejected more often than identical unfair offers by computerized agents. The effect of agency on the relation between arousal and behavior is not stated explicitly in that study, but it can be assumed 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, 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, whereas rejection was related to high skin conductance levels. 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. Hypothesis 5 states:

Hypothesis 5. *The relationship between overall arousal and bids is mitigated by low agency.*

Authors (year)	Task, Description	Dependent Variables	Independent Variables	Med./Mod. and CVs	NeuroIS Method	VL	coop	comp	GR	$	#
Gallagher et al. (2002)	Playing “stone, paper, scissors” against a computer/ a human; guessing the other’s choice	Anterior paracingulate cortex, inferior frontal cortex, and cerebellum activation	Framing towards mentalizing/ rule solving	-	fMRI			x			9
Williams and 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 and 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	x		134
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 and 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, HR, SCR, R	Opponent (friend/ computer), difficulty (beginner, easy, medium, difficult)	-	HR, SCR, R	x		x			8 10
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

Authors (year)	Task, Description	Dependent Variables	Independent Variables	Med./Mod. and CVs	NeuroIS Method	VL	coop	comp	GR	$	#
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)	Winner’s curse in electronic auctions	Bids	Agency	-	-			x		x	47 48
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 and 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, cooper-ation/ competition	-	HR, SCL, SCR	x	x	x			32
von der Pütten et al. (2010)	Answering questions to a conver-sational 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
Appel et al. (2012)	Text-chat with another partici-pant, 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 pic-tures; 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, SC					x	103

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

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

3 | Experimental Design

Our experiment includes two treatments. First, in the *high agency* (HA) treatment, the participants interact with human opponents only. Second, in the *low agency* (LA) treatment, the participants interact with computerized opponents only. The computerized bidders in the LA treatment replicated the bids of the human bidders. The LA treatment sessions were conducted one week after the HA treatment sessions. By replicating the human bids, we avoid influencing the results due to differences in bidding by the agents. This makes the results comparable across treatments (see Van den Bos et al. (2008) for a similar approach). Participants in the LA treatment thus faced the exact same bids from their opponents as participants in the HA treatment. Therefore, the only difference between treatments is that bidders know that they interact with human opponents (HA) or computer opponents (LA), respectively. There are no graphical representations of the bidders. Note that to avoid order effects our experiments is based on a between-subjects design, i.e., subjects either participated in the HA or LA treatment, but not both.

During the experiment, each bidder takes part in a sequence of 30 FPSB auctions with 2 other bidders. The FPSB auction is particularly suited for our study, as (i) it belongs to the class of static auctions and thus enables us to maintain a high level of control with little path dependence, (ii) the impact of computerized agents can be investigated in a scenario with little interaction, and (iii) the FPSB auction format is frequently used in markets world-wide. In the HA treatment, participants are randomly reassigned to groups of 3 bidders before every single auction period (random stranger matching). Thus, a subject does not know which other participants are currently participating in the same auction. Each group then plays a single FPSB auction independently with 3 bidders (see Engelbrecht-Wiggans and Katok (2008); Katok and Kwasnica (2008), and Astor et al. (2013) for similar approaches). After each period, the participants were rematched into different groups of 3, which was communicated in the instructions, so that no insights about specific participants could be gained and carried over to the next interaction with a specific participant. In the LA treatment, every participant was matched with 2 computerized bidding agents, which replicated the human bids from the HA treatment one week earlier. Here also, every participant was re-matched into a different group with 2 computerized bidding agents after each auction period.

Auction Process

Before an auction starts, each bidder i is informed about his or her independent private value (IPV) v_i for the commodity to be auctioned.[8] This IPV is independently drawn for each bidder from a uniform distribution with support on the discrete integer interval $\{11, 12, \ldots, 109, 110\}$ and is expressed in monetary units (MU). The bidders only know that there are 3 bidders in each auction, their own IPV and the general distribution of IPVs, which is the same for all bidders. The bid of participant i is denoted by b_i. The winning bidder i receives a payoff equal to the winning bid minus his or her individual valuation for the commodity being auctioned (v_i - b_i). All other bidders receive 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 $b(v_i)^* = \frac{2}{3} \cdot (v_i - 10) + 10$ (Krishna, 2002).

In order to exclude missed-opportunity and money-left-on-the-table effects (Engelbrecht-Wiggans and Katok, 2008), the bidders are presented a minimal information environment, in which they are neither informed about the highest nor the second-highest bid (Van den Bos et al., 2008). At the end of an auction, bidders only receive information on whether they have won the auction or not, and their payoff. The bidders' identities are not revealed. In order to capture the physiological reactions to specific events throughout the auction process, information is provided in timed intervals of at least five seconds (Sanfey et al., 2003). In particular, we investigate the intensities of the bidders' immediate emotions in response to three specific events in the auction process (E1, E2, and E3). More specifically, we first assess the bidders' physiological responses to placing a bid (E1). Then, the bidders see an information screen that informs them that the auction outcome will be revealed soon (E2). Finally, the bidders find out whether they have won or lost the auction (E3). The auction process is summarized in Figure 2.

Procedure

Altogether, 27 female and 93 male participants (6 participants per session, 120 in total, mean age = 23.16 years) participated in 20 sessions. There were 12 sessions in the HA treatment, and 8 sessions in the LA treatment (N_{HA}=72, N_{LA}=48). The experiment was conducted at [anonymized] and in accordance with the university's ethics guidelines. It was implemented using the z-Tree environment (Fischbacher, 2007). The participants were recruited from a pool of undergraduate students using the ORSEE software environment (Greiner, 2004). There was no lump sum payment. The experimental currency was monetary units (MU) with 16 MU being equivalent to €1.00. Depending on their individual performance, all of the gains and losses accumulated during the auctions went to the bidders' individual accounts, which were individually paid out in cash to the participants at the

[8] 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 her 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 her chances of winning against the nominal payoff in case of winning the auction. This is based on her own IPV and the available information on the distribution of the other bidders' IPVs.

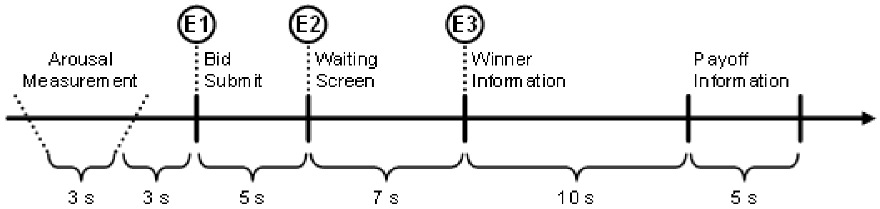

Figure 2: *Auction Process and Timed Intervals Between Auction Events*

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) in order 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 were able to earn up to an additional €3.85. Each participant selects one of two lotteries from 10 different specifications each with a different level of risk and expected payoff. Based on how often the participant chooses the less risky lottery, he or she can be classified as risk averse or not risk averse. Before the first auction started, a five-minute resting period was introduced for calibration purposes (Riedl et al., 2014). In order to ensure comprehension of the rules of the experiment, the participants then had to successfully complete a quiz regarding the experimental instructions and performed five practice auctions, in which gains and losses were not considered. In order to avoid artifacts due to body movements, participant interactions with the experimental system were limited to mouse inputs, i.e., only the dominant hand was needed. Participants were equipped with a pair of earmuffs to avoid the influence of background noise. During the experiment, we continuously measured the bidders' HR and SCR. HR is derived from an electrocardiogram (ECG) recording device using a lead I method with single-use electrodes placed on the left and right wrist (Berntson et al., 2007). Skin conductance was recorded using a constant current amplifier measurement system and Ag/AgCl (silver/silver chloride) electrodes. The electrodes were attached 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). All the sessions were conducted within a period of two weeks with an average relative humidity of 53.1% 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). The physiological measurement results of 17 participants had to be removed 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, the analysis is conducted using a data sample of 120 − 17 = 103 participants (N_{HA}=64 [51 male, 13 female], N_{LA}=39 [29 male, 10 female]). The analysis of allocation efficiency, however, is based on an auction level and therefore includes the bids of all 120 participants.

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 which 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., 2014; vom Brocke and Liang, 2014). While each of these approaches has distinct advantages, we focus on HR and SCR, because these measures (i) provide insights into participants' immediate emotions and overall arousal, (ii) require little measurement overhead and can thus be assessed for several participants simultaneously, which is a necessary prerequisite for interactive economic experimentation, and (iii) are measurable unobtrusively, as they do not demand electrodes attached to the face or the scalp (such as, 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) 6 to 3 seconds textitbefore they placed a bid relative to the individual baseline level of HR during the five-minute resting period (see for Smith and Dickhaut (2005) and Adam and Kroll (2012) a similar approach). An arousal parameter of x% percent in this context thus means that a participant's HR in the time frame of 6 to 3 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. The last 3 seconds before bid submission are not included in the computation of θHR, because previous research found that participants exhibit deceleratory HR responses in this time frame due to preparation of imminent action (Jennings et al., 1990). In contrast, SCR is a measure that directly reflects the activity of the sympathetic nervous system only (Bechara and Damasio, 2005; Dawson et al., 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), i.e., the ongoing emotional state. In comparison to θHR, however, changes in SCL are rather inert and we thus 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. The amplitude of an SCR (SCR.amp) has been identified as a proxy for the intensity of immediate emotions and reflects short bursts of sympathetic activity (Dawson et al., 2011). In this study, the SCR.amp values were obtained by decomposing skin conductance into its tonic and phasic components with the Ledalab analysis software (Benedek and Kaernbach, 2010). Only amplitudes that occur one to three seconds after each event and amplitudes greater than or equal to a value of .01 μS were used (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

This section presents 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). Then the interplay of agency, overall arousal and bidding behavior is analyzed (H3–H5). Finally, we expand on the impact of agency on allocation efficiency.

Immediate Emotions during the Auction Process (H1)

This section considers 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 hypothesized that the intensities of such immediate emotions are mitigated when agency is low (H1). In the analysis, we additionally take into account the impact of the IPV as well as the outcome role (winning or losing). For the purpose of illustration, the IPV values are grouped into five categories, which are summarized in Table 2.

Figures 3, 4, and 5 display the bidders' average SCR.amp in response to the 3 auction events E1, E2, and E3. The results are grouped by value class and treatment. All of the figures indicate that emotional intensity is generally lower in the low agency treatment, and generally higher for higher value classes. The strongest responses are triggered by displaying the auction outcome (E3), whereas E1 and E2 trigger less intense responses. To confirm the graphical evidence, four generalized least squares (GLS) regressions are conducted, in which each bidder's SCR.amp in response to E1, E2, and E3 is modeled. We use a between subjects design as is common in experimental setups. This means that we are comparing the results of a group of subjects in one group to a different set of subjects in our control group. We sample the same participants in the same treatment multiple times and account for level differences using control variables (gender and risk-aversion). We treat our subjects with two levels of agency, unfortunately we cannot treat our subjects with every possible level of agency and therefore estimate a model that includes random effects to account for this. We estimate a GLS mixed-model that simultaneously accounts for both random effects and fixed effects. The regressions are conducted for each auction using robust standard errors clustered by subject. For all events we account 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 × auction outcome).

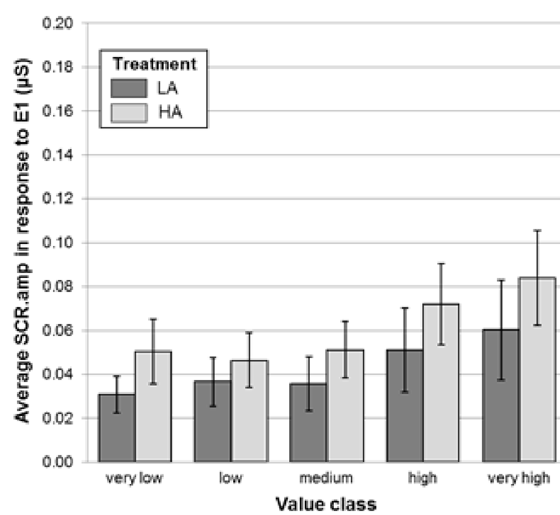

Figure 3: *Average SCR.amp in Response to E1*

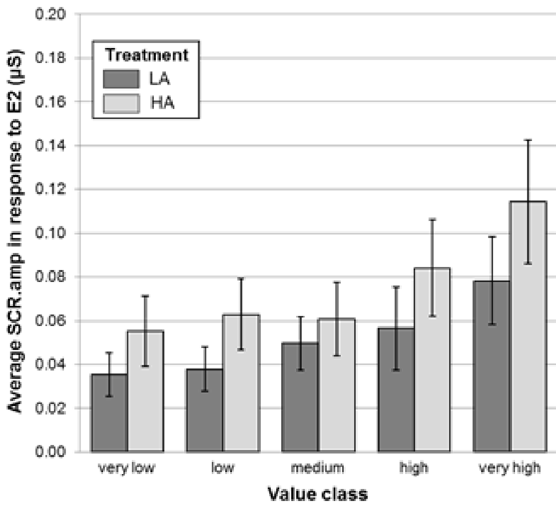

Figure 4: *Average SCR.amp in Response to E2*

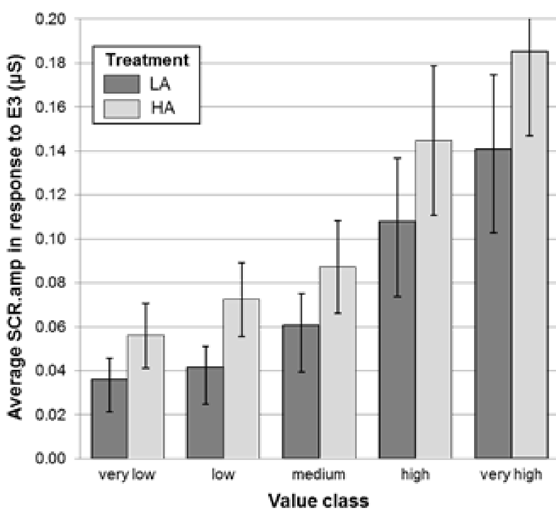

Figure 5: *Average SCR.amp in Response to E3*

The results of the GLS regressions are summarized in Table 3.[9] First, the general positive relationship between stakes and emotional intensity can also be confirmed in this setting. The coefficient of value class is positive, significant, and consistent for E1–E3. Thus, the intensity of the bidders' immediate emotions in response to salient auction events is higher for higher value classes. Second, we observe that emotions are stronger when bidders experience higher levels of overall arousal (θHR). In other words, there is a positive relationship between overall arousal and the intensity of immediate emotions, which is consistent for E1–E3. Third, the differences in the intensities of the emotional responses between the LA and HA treatments are 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 is stronger than at E1 and E2. Note, however, that the coefficient is only marginally significant for E1. In summary, the null hypothesis can be rejected in favor for hypothesis H1. The intensity of the bidders' immediate emotions in response to salient auction events is lower for low agency than it is for high agency.

With respect to the impact of outcome role on immediate emotions in response to E3, it is important to highlight that the bidders cannot lose money in our setting. Thus, the status quo is maintained when an auction is lost, whereas a gain is realized when an auction is won. One could thus 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* is positive and significant (*b=.020, p=.004*). Hence, the intensity of the bidders' immediate emotions in response to the auction outcome is higher if the auction is won. As depicted in Figure 6, the general intensity of emotions in response to E3 is higher in the HA treatment and the responses are stronger for winning an auction.

An interaction effect between treatment and auction outcome cannot be observed: winning an auction (compared to losing) causes stronger responses across both treatments and participants in the HA treatment show stronger responses to both winning and losing the auction than the participants in the LA treatment. Interestingly, however, we observe that winning an auction in the LA treatment causes stronger responses than losing an auction in the HA treatment. We return to this point in the discussion.

[9]Note that with 103 participants and 30 auctions a total number of $103 \times 30 = 3090$ 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 time frame due to movement artifacts or due to a sudden noise on the signal. Therefore, the total number of observations is $3090 - 23 = 3067$.

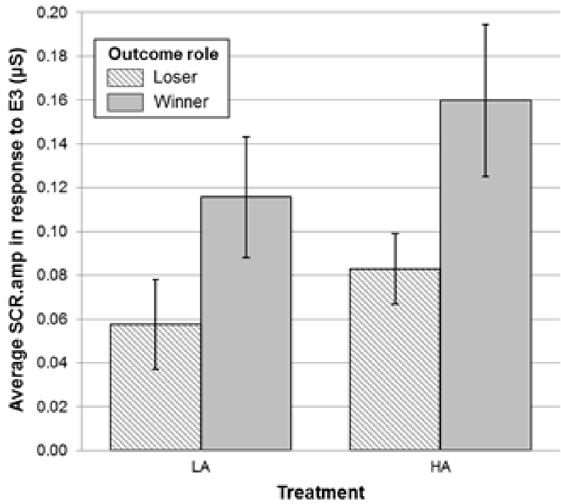

Figure 6: *Average SCR.amp in Response to E3 for Different Outcome Roles and Treatments*

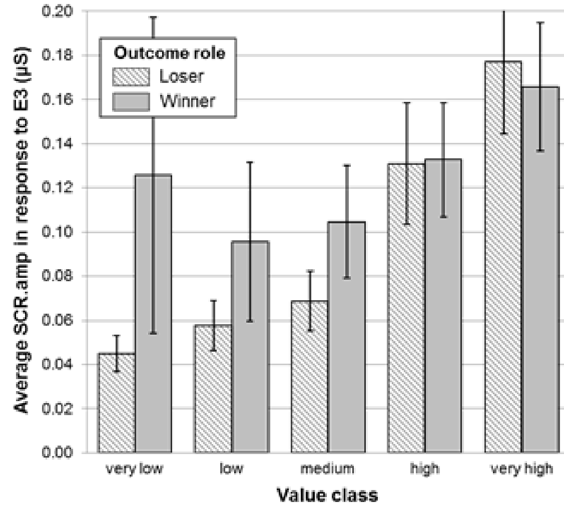

Figure 7: *Average SCR.amp in Response E3 for Different Outcome Roles and Value Classes*

Figure 7 displays the impact of outcome role and value class on average SCR.amp, indicating that losing despite a high or very high valuation has 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) is significant ($\chi^2(1)$=8.135, *p<.01*). The coefficient for the dummy winner is positive and significant (*b=.042, p<.001*), i.e. at the lowest value class (coded as 0), winning causes stronger emotional responses than losing. The coefficient of the variable for value class is also positive and significant (*b=.008, p<.001*), i.e., in case that an auction is not won, every increase in value class will increase the emotional response significantly. The interaction term (winner × value class) is negative and significant (*b=-.003, p=.004*), i.e., the just mentioned increase is lower, but still positive (*.008 + (-.003) = .005*) if the auction is won. This pattern is consistent across treatments. This point will also be discussed in more detail in the discussion.

Overall Arousal during Bidding (H2)

This subsection considers 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 can observe that arousal levels are marginally higher in the HA treatment than they are 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, it is important to highlight that bidding behavior for low valuations is rather different than it is for high valuations (Engelbrecht-Wiggans and 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 it 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 are much less intense for low valuations. Therefore, in the following analysis only auctions with IPV equal to or higher than 60 MU, i.e., the upper 50% of the IPV distribution are used. This means that from the series of 30 auctions a subject participated in, on average roughly 15 auctions are considered in the analysis.

Correspondingly, Figure 8 depicts the bidders' average θHR across all auctions in which their IPV is equal to or higher than 60 MU. When comparing the bidders' θHR in those auctions, we can observe that overall arousal levels are significantly higher in the HA treatment than they are 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 confirmatory of the results on immediate emotions, participants

Dependent Variables: SCR.amp at Different Events (E1–E3)

		(1) E1			**(2) E2**			**(3) E3**			**(4) E3**	
Independent Variables	Beta	Coeff.		Beta	Coeff.		Beta	Coeff.		Beta	Coeff.	
Dummy: LA Treatment	-.070	-.015	$^+$	-.091	-.022	*	-.102	-.030	*	-.102	-.030	*
		(.008)			(.009)			(.013)		(.013)		
Dummy: risk averse	.058	.015		.031	.009		.011	.004		.011	.004	
		(.009)			(.012)			(.018)		(.018)		
Dummy: female	-.095	-.023	*	-.111	-.032	**	-.124	-.043	**	-.123	-.042	**
		(.009)			(.011)			(.014)		(.014)		
$(\text{Value class})^2$	.122	.002	***	.160	.003	***	.281	.007	***	.331	.008	***
		(<.001)			(<.001)			(.001)		(.001)		
Auction (#1–30)	-.042	<.001	*	-.090	-.001	***	-.063	-.001	**	-.061	-.001	**
		(<.001)			(<.001)			(<.001)			(<.001)	
Overall arousal (θHR)	.050	.001	**	.046	.001	**	.044	.001	**	.042	.001	**
		(<.001)			(<.001)			(<.001)			(<.001)	
Dummy: winner							.067	.020	**	.139	.042	***
								(<.007)			(<.009)	
$(\text{Value class})^2 \times$ winner										-.119	-.003	**
											(<.001)	
Constant		.036	***		.061	***		.069	***		.065	***
		(.010)			(.014)			(.019)			(.019)	
		N = 3067			N = 3067			N = 3067			N = 3067	
		$R^2 = .039$			$R^2 = .063$			$R^2 = .148$			$R^2 = .150$	

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

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

are less aroused when they are bidding against computer opponents.

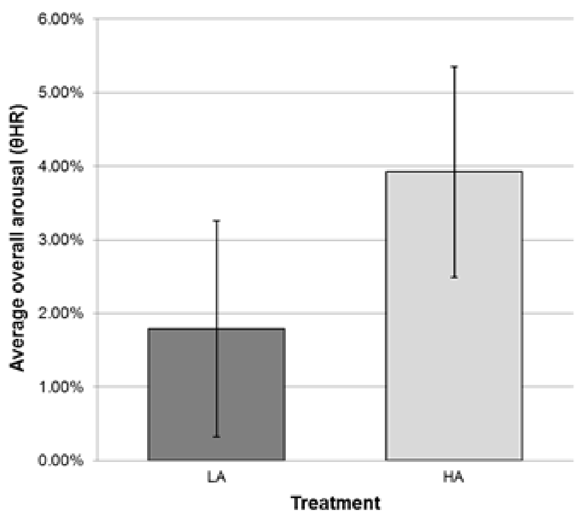

Figure 8: *Average Overall Arousal (θHR)*

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

Based on the literature, we hypothesized that there is a relationship between bidders' arousal and bidding behavior for high agency (H4), while this relationship is mitigated for low agency (H5). In order to test this relationship, we first analyze the Pearson correlations between arousal and bids grouped by treatment.[10] The analysis reveals a statistically significant negative correlation between arousal and bids (*n=64, r=-.213, p=.046*, one-tailed) in the HA treatment, whereas there is 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 very simple setting. While compelling, the previous results may not hold up to more rigorous analysis. In order to control for other known effects on bidding behavior, we perform a mediation analysis based on our research model (cf. Figure 1) and also test the conditional indirect effect. The analysis is conducted according to the mediation analysis approach of Krull and MacKinnon (2001). The GLS regressions summarized in Table 4 are conducted on the level of single auctions using robust standard errors clustered by subject. The independent variables are treatment (LA: 1, HA: 0), sex (female: 1, male: 0), bidders' arousal (θHR), and whether or not subjects are classified as risk averse (1: risk averse, 0: not risk averse) based on the questionnaire of Holt and Laury (2002). Additionally, we control for valuations and auction sequence.

Consistent with our previous analysis and thus providing further support for H3, specification (1) shows that arousal is 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 place lower bids in computer markets (*b=-3.101, p=.002*). Testing H4 and H5, we find that bidders place lower bids when they are aroused (b=-.110, p<.001), while this effect is conditional on whether agency is high or low (*b=.111, p=.004*). Moreover, a Wald test confirms that the increase in explanatory power from specification (2) to specification (3) is significant ($\chi^2(2)=20.706$, *p<.001*). Note that these results are robust against using different time frames (cf. Appendix A).

[10] As outlined in the last subsection, the analysis is based on auctions with IPV equal to or higher than 60 MU, i.e., the upper 50% of the IPV distribution.

Figure 9 illustrates the relationship between arousal and bids grouped by treatment. We see that in the LA treatment the average bid appears to be completely invariant to arousal. The HA treatment differs markedly and exhibits decreases in average bid between low and high arousal. It appears as if the participants are not only more aroused when they are bidding against other humans but that their bidding behavior is correlated with arousal. This is also reflected in an interaction term between LA and arousal (*b=.111, p=.004*). In order to test the significance of this conditional indirect effect of arousal on bids, conditional for agency, we conduct a bootstrapping analysis. Based on 5,000 bootstrapped samples using bias-corrected 95% confidence intervals, the analysis reveals 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% confidence interval. Since zero is not in the 95% confidence interval, the indirect effect is significantly different from zero at p<.05 (two-tailed). In contrast, the corresponding analysis for low agency reveals that the indirect effect is not significant (*IE=-.027, SE=.489, LL=-1.020, UL=.913*). These results are also summarized in Table 5.

Taken as a whole, we reject the null hypotheses in favor for our research hypotheses H3, H4, and H5. In the traditional context of markets with high agency, bidders are more aroused and this arousal is also directly reflected in their bids. In markets with low agency, however, bidders are less aroused and the indirect effect of arousal on bids disappears. In other words, low agency mitigates both arousal as well as the relationship between arousal and behavior. At this stage, it is important to highlight though that it remains unclear whether the mediating role of arousal is due to a causal relationship of arousal on bids or because bidders who place lower bids against other human bidders are also more aroused. We will return to this point in the limitations section.

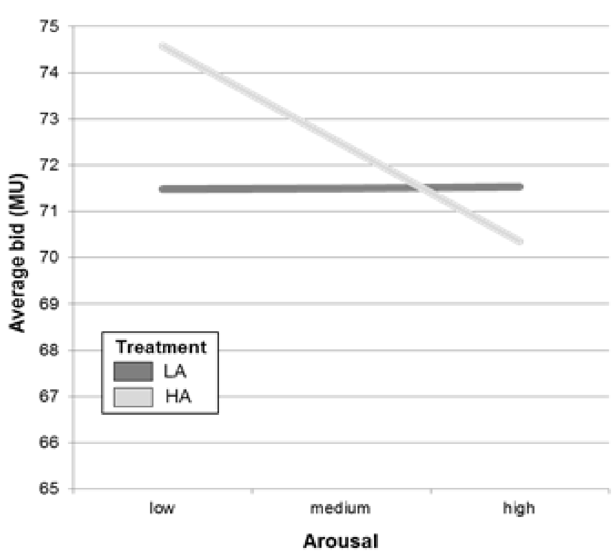

Figure 9: *Relationship between Overall Arousal and Bids*

Treatment	Indirect Effect	Boot SE	$LL_{95\%CI}$	$UI_{95\%CI}$
High Agency	.447	.072	.037	.589
Low Agency	-.027	.490	-1.020	.913

Table 5: *Indirect Effects for HA und LA Treatment*

Allocation Efficiency

The results thus far have focused 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 consider an auction to be efficient if the bidder with the highest IPV wins the auction. In the case of a tie in terms of IPV, the auction is efficient if any of the highest IPV bidders wins the auction. If bidders submit the same, highest bid, the winner is determined randomly. This auction is regarded as efficient, with a weight corresponding to the ex-ante chances of winning the auction for the bidder with the highest IPV. The efficiency results for the HA and LA treatment are summarized in Table 6.

Treatment	# efficient	# total	efficient	not efficient
High Agency	657.5	720	90%	10%
Low Agency	427	480	89%	11%

Table 6: *Allocation Efficiency for HA and LA Treatment*

Overall, roughly 9 out of 10 of the auctions were efficient. Broken down by treatments, the results show only little difference. Auctions with high agency are efficient in 89% of the cases. Auctions with low agency are efficient in 90% of the cases. The difference is not significant at any conventional level (χ^2 - test, *p=.590*). It appears that despite the fact that participants are more aroused overall in auctions with high agency, there is 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 efficiency is not the original focus of our study, 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

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 monitoring market activity continuously. The presence of computer

	Dependent Variables								
	(1) Arousal			**(2) Bid**			**(3) Bid**		
Independent Variables	Beta	Coeff.		Beta	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 (.015)	***	.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.
$^{+}\,p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 4: *GLS Regression Models for Overall Arousal and Bids*

agents affects the way humans perceive their environment, which is captured by the notion of *agency*. In recent years, and beyond cooperative and communicative interaction, computer agents have also become *competitors* to humans, for instance in trading or auctions (Brogaard et al., 2014; Hendershott et al., 2011). In this work, we have analyzed the interplay of agency, affective processes, and bidding behavior in FPSB auctions in a controlled laboratory experiment, in which subjects compete 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) are weaker for low than for high agency (H1). Emotional intensity depends on the bidders' individual valuations and is particularly strong in response to winning an auction. Bidders' overall arousal levels are lower when bidding against computerized agents (H2). We find that, overall, bidders submit lower bids in the low than in the high agency condition. Moreover, agency and overall arousal affect bidding in another, interactive way: While higher degrees of overall arousal are associated with lower bids for high agency (H4), this relationship is mostly mitigated in the low agency treatment (H5). In other words, there is an indirect effect of overall arousal on bidding behavior, which is conditional on agency: computer opponents appear to mitigate bidders' emotionality during the auction.

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., 2009), 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 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 and Benbasat, 2010). In our setting, the opponents' gender was not known to subjects. 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. Differences in overall arousal were not observed. This may be seen as an indication for a less reward-driven nature of female compared to male bidders–which is reflected in both higher bids and less pronounced immediate emotions in response to auction events. Interaction effects between gender and the relationships investigated in our research model were not observed.

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 et al., 2000; Deng and Poole, 2010). In general, emotional experience plays an important role for Internet auction site sponsors as it distinguishes them from fixed-price competitors (Ariely and Simonson, 2003; Lee et al., 2009). For bidders in consumer auctions, emotional experience can even be seen as a source of hedonic value (Childers et al., 2001). Single design elements of websites can promote or mitigate affective processes in the user which in turn affect their behavior and general attitude towards the platform (Cronin et al., 2000; Deng and Poole, 2010). Menon and Kahn (2002, p. 39) argued that online marketers can use "very pleasing, enjoyable stimuli to encourage browsing and receptivity to impulse shopping." In this sense, the platform should be designed to be experienced positively, in order to create hedonic value for the customer. Auction format is one way to induce immediate emotions. When comparing our results with other studies, it becomes evident that different auctions formats are associated with different emotional intensities. Adam and Kroll (2012) found that in Dutch auctions, the frustration of losing is experienced relatively stronger than the respective joy of winning. In contrast, our results, in line with the results of Astor et al. (2013), show that the joy of winning a FPSB auction is 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) argued that, if bidding itself is arousing, this can "feed a vicious cycle of bidding and overbidding." Thus, in dynamic auctions, such emotions may eventually promote higher payoffs for the auctioneer. E-bay, for instance, is practicing this by alerting bidders immediately via email when another bidder has outbidden them.

Third, agency and overall arousal are related to behavioral patterns that can be exploited by the auction platform operator. In particular, bidders seem to engage in socially competitive bidding in high agency settings, trying not only to win the commodity at stake, but also to beat their peers. This 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 in order to inflate prices. For this purpose, the platform operator can increase or decrease the bidders' arousal, e.g., by 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 et al. (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. This should be taken into account by regulatory authorities as well as by the human traders and the organizations they represent.

Finally, from the perspective of market participants, our results show that their behavior is related to their overall arousal. There is reason to believe, that market participants can benefit from an awareness and active consideration of this relationship. Since we measure 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, acceptance or rejection of 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 in order 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 in order to make better decisions (vom Brocke et al., 2013).

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 suggests that human behavior is less driven by emotional factors in low agency settings, which is consistent with previous results on bargaining (Ben-Shakhar et al., 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 to the socially competitive nature of auctions (Adam et al., 2011; Ku et al., 2005), i.e. bidders strive to win a social competition against their peers, rather than merely gaining a material surplus. Everything else equal, higher arousal is associated with lower bids. Our study demonstrates that this only holds for the high agency treatment. Thus, as outlined in our research model, the factors agency and arousal interact, where low agency mitigates arousal per se, as well as 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 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 provides support for the theories based on "equating the reference point with expectations rather than the status quo" (Kőszegi and 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 the own IPV, and thus the chances of winning, were comparatively high ex-ante. Our results confirm this notion. We find that the frustration of *not winning* even exceeds the joy of winning for the higher value class slightly. In our regression analysis, this effect is accounted for using the interaction term *value class* × *dummy winner* (see Table 3). The effect is 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) argued 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 With regard to agency, we find 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, this can be seen 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, this can also be seen as an indication that the joy of winning an auction in the low agency treatment does not only stem from the monetary reward, but 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 would be in line with the reasoning of (Nass and Moon, 2000) that computers can take on the role of social actors.

Also 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 implies that in those moments the bidders experience immediate emotions in response to *thinking* about past or future events (Bechara and 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, 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 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 the user. Such processes may have important ramifications for website and interaction-process design, perception, and success (Cronin et al., 2000; Deng and Poole, 2010).

Limitations and Future Research

There are several limitations to this study. First, and most importantly, the experiment focuses on FPSB auctions; "leaving 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 the use of dividing blinds and earmuffs and only interact very indirectly by exchanging sealed bids. It is thus advisable 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 submit single bids in FPSB auctions. Future research may therefore also take affective processes in response to repeated bidding in the same auction into account, addressing effects of pseudo-endowment (Ariely and Simonson, 2003) and bidders' attachment (Kőszegi and 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 et al., 2010; Davis et al., 2009; Fox et al., 2014; Nunamaker et al., 2011; Riedl et al., 2011, 2014). In this regard, several prior studies explicitly disentangled 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 and 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).[11] It is important to note, however, that beyond the role of recommender agents, providing consumers with advice on products (Benbasat et al., 2010), some entertainment shopping platforms now actually start to make use of avatars or other forms of graphical representations (e.g., dealdash.com) in order 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 in order to disentangle the effects related to agency from those related to social cues, e.g., by displaying actual photos or stylized representations. In order 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 and 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).

A third limitation is that, although our analysis reveals a mediating role of overall arousal, a reliable conclusion about causality from arousal to bids is not possible. Even though arousal was measured in the time frame 6 to 3 seconds *before* the bid was submitted, it might very 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 disappears when the bidders face computer opponents. In order to further disentangle this effect, future research may induce different levels of arousal independent of the auction process. This may be achieved, for instance, by letting subjects play an arousing game, listen to arousing

[11] 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 and Blascovich (2004).

music, or experience stress prior to engaging in the auctions (Riedl et al., 2012, 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 et al., 1995). Due to the nature of our experiment, requiring the presence of at least 3 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 and Webster, 2013) to shed more light on (i) the bidders' cognitive processes (e.g., cognitive load, strategies, and motives), and (ii) 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., 2014). Providing strong evidence for the importance of unconscious processes in the context of agency, Fox et al. (2014, p. 25) found in a meta-analysis of 32 studies that "objective measures revealed greater differences for agency than subjective measures." Using electroencephalography as an objective measure of cognitive load and valence (Gregor et al., 2014; Ortiz de Guinea and Webster, 2013) thus seems to be a promising complementary approach in this context.

Conclusions

Taken as a whole, our study shows that the intensity of bidders' immediate emotions and overall arousal as well as 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, there is 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 A

Different Windows Sizes for Arousal Computation

In the analysis, we used the time window of 6 to 3 seconds *before* submitting a bid for computing overall arousal, i.e. a time window of 3 seconds and a buffer of 3 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.

Independent Variables	Overall Arousal (Window Size for Overall Arousal) (1+5)		(2+4)		(3+3)		(4+2)		(5+1)	
Dummy: LA Treatment	-2.257	*	-2.237	*	-2.304	*	-2.262	*	-2.170	*
	(.974)		(1.012)		(1.049)		(1.055)		(1.048)	
Dummy: risk averse	-2.216	+	-2.210	+	-2.298	+	2.405	*	-2.430	*
	(1.146)		(1.192)		(1.219)		(1.055)		(1.048)	
Dummy: female	-.228		-.246		-.240		-.129		-.087	
	(1.339)		(1.312)		(1.344)		(1.348)		(1.338)	
Valuation	.039	*	.042	*	.0440	**	.045	**	.046	**
	(.018)		(.017)		(.016)		(.016)		(.015)	
Auction (#1–30)	-.174	***	-.175	***	-.168	***	-.158	***	-.151	***
	(.018)		(.017)		(.016)		(.016)		(.015)	
Constant	5.045	**	4.815	**	4.556	*	4.298	*	3.899	*
	(.018)		(.017)		(.016)		(.016)		(.015)	
	N = 1506		N = 1506		N = 1506		N = 1506		N = 1506	
	$R^2 = .047$		$R^2 = .049$		$R^2 = .051$		$R^2 = .052$		$R^2 = .054$	

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 7: *GLS Regression Models for Overall Arousal with Different Window Sizes*

Appendix B

[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 1). [The computerized bidding

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

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

Table 8: *GLS Regression Models for Bids with Different Window Sizes for Overall Arousal*

agents bid simultaneously and do not know about other bids.]

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.

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