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SPECIAL ISSUE PAPER

# Affective engagement to emotional facial expressions of embodied social agents in a decision-making game

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## ABSTRACT

Previous research illustrates that people can be influenced by the emotional displays of computer-generated agents. What is less clear is if these influences arise from cognitive or affective process (i.e., do people use agent displays as information or do they provoke user emotions). To unpack these processes, we examine the decisions and physiological reactions of participants (heart rate and electrodermal activity) when engaged in a decision task (prisoner's dilemma game) with emotionally expressive agents. Our results replicate findings that people's decisions are influenced by such emotional displays, but these influences differ depending on the extent to which these displays provoke an affective response. Specifically, we show that an individual difference known as *electrodermal lability* predicts the extent to whether people will engage affectively or strategically with such agents, thereby better predicting their decisions. We discuss implications for designing agent facial expressions to enhance social interaction between humans and agents. Copyright © 2012 John Wiley & Sons, Ltd.

**KEYWORDS**
affective engagement; physiological signal analysis; emotional facial expressions of agents; decision-making game

*Supporting information may be found in the online version of this paper.*

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## 1. INTRODUCTION

Recently, there has been an increase in the development of embodied social agents that express emotional facial expressions [1–3]. Prior studies have shown that emotional facial expressions affect human decision making in human–agent interactions [4–13]. For instance, De Melo and colleagues showed that agents expressing certain facial expressions can reliably alter people's willingness to make concessions in negotiations [6] and their tendency to cooperate in social dilemmas [7]. These findings are tantalizing, because they reinforce more general findings that people treat computers as social actors [14] when they include appropriate social cues. This paper attempts to shed new light on the influence of such emotional displays by illuminating the mechanisms by which they achieve their effects. Specifically, we aim to tease apart alternative theories of how computer emotion might impact human–computer interaction, thereby giving greater insight into the appropriate design of such systems.

Research on human emotion has offered two basic theories on how emotion displays might influence human-to-human interaction, and we draw on these for our investigation of human–agent interaction. One theory argues that emotional facial expressions provide *information* about the other party's beliefs, desires, and intentions, and people rationally use this information to reach social decisions [4–10]. The other theory argues that emotion begets *emotion*: that is, expressions by one party evoke emotions in the other, and these evoked emotions influence decision making [11–13,15–20]. To assess this, researchers have analyzed people's physiological states in response to emotional expressions [15–20]. They found that people respond to negative emotional expressions with increased skin response and decreased heart rate (HR) deceleration [15,18]. However, this prior work has not examined the complete linkage between agent expressions, evoked emotions and decision making.

To differentiate these two alternative explanations—in other words, do people affectively or cognitively engage with expressive animated agents—we examine people's physiological responses to agent expressions in the context of a social dilemma (i.e., prisoner's dilemma). We consider two related questions: (1) do people respond emotionally to agent facial expressions? and (2) how do these felt emotions influence their decisions?

For the first question, we examine people's physiological responses to specific expressions when compared with agents that do not show an expression in the same situation. For example, if subjects play with an agent that smiles when they cooperate, do they show more arousal and positive valence than subjects that play with an agent that does not smile?

To gain insight into the second question, we examine individual differences in how people react to emotional stimuli. Specifically, if we hypothesize that felt emotions cause different decisions, then subjects should make different decisions depending on how emotional they become. Using a personality difference known as *electrodermal lability* [21], we divide subjects into 'highly sensitive' and 'less sensitive' groups on the basis of their physiological reactions to the International Affective Picture System (IAPS) [22]. We hypothesize that highly sensitive subjects are more likely to feel emotions and act upon them, thus giving some insight into the causal relationship between felt emotion and social decisions with computer agents.

## 2. RELATED WORK

### 2.1. Facial Expressions of Embodied Agents and Decision Making

Many researchers have studied emotional facial expressions of humans and their effect on decision making [4,5]. Previously, Kopelman *et al.* [4] observed that strategic displays of positive, negative, and neutral emotions in negotiations had an effect on decision making in a negotiation task. Scharlemann *et al.* [5] also observed an effect of smiling on decision making in a matched pair proportions test. They found that facing a negotiator displaying negative facial expressions led to more extreme demands. In addition, smiling significantly increased the users' belief about the trustworthiness of their counterparts and affected their cooperative behavior. These results suggest that human emotional facial expressions provide information that people use in their social decisions.

As an extension of this research on the impact of emotion expression in human-to-human interaction, researchers have explored the effect of emotional facial expressions of agents on human decision making [6–10]. De Melo *et al.* [7] observed that agent's facial displays impacted people's decision to cooperate in the prisoner's dilemma game. Yuasa *et al.* [8] found that agents' facial expressions had a significant effect on people's impressions of friendliness, trustworthiness, and dominance. This work suggested that agents' facial expressions had similar effects on decision making as human facial expressions by increasing or decreasing positive impressions.

However, these studies focused on how conscious cognitive processing could explain people's cooperative behavior when people engaged with agents that display emotional facial expressions. Many of these results were based on subjective questionnaire data. However, drawing conclusions from questionnaire data alone has, at least, two disadvantages: first, questionnaires may not reflect the users' response in real time; second, because questionnaires are given after the interaction with agents, they measure responses on the basis of the users' memory. Physiological measures address both of these limitations because they measure real-time and nonconscious processing.

### 2.2. Physiological Response to Facial Expressions of Embodied Agents

Previous researchers monitored physiological responses to assess the underlying process in human decision making. They observed that unfair or unreciprocated cooperation elicited negative feelings by monitoring certain brain region activation [13,15,16]. Pillutla *et al.* [13] indicated rejection behavior related to anger. Haruno *et al.* [15] and Rilling *et al.* [16] found that unfair or unreciprocated cooperation with a computer agent (or human partner) elicited negative feelings observed from the activation of amygdala. These prior observations are related to the somatic marker hypothesis that indicates a positive correlation between bodily signals, experience of emotions, and decision making [23].

In addition, some researchers observed feelings by monitoring the autonomic nervous system when people played a decision-making game [17–20]. Bechara *et al.* [17] found that rejecting unfair offers led to anterior insula activation as well as increased electrodermal activity (EDA) in an ultimatum game. Ohira *et al.* [18] found that HR decreased faster after an unfair offer than after a fair offer in an ultimatum game. Wout *et al.* [19] also found higher skin conductance activity for unfair offers in an ultimatum game, and they concluded that these results were associated with the rejection of unfair offers.

Furthermore, researchers analyzed autonomous responses when people interacted with emotionally expressive agents. Prendinger *et al.* [24] showed that agents' emotional expressions such as sorry or happy were related to increased EDA and lower stress. However, it is still not clear how emotional facial expressions of agents affect physiological processing of emotional stimuli as well as decision making. To address this, we measure HR and EDA on a standard emotional perception task. We then study how these measures relate to physiological measures when users interact with agents in a social dilemma.


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# 3. METHOD

## 3.1. Experiment Design

By monitoring physiological signals, we aim to assess the extent to which participants are affectively engaged with expressive agents in a social decision-making game, the prisoner's dilemma. In this version of the prisoner's dilemma, players can invest money or credit in one of two projects: green (cooperation) or blue (defection). The game, thus, has four possible outcomes: mutual cooperation (CC), when a subject cooperates and an agent cooperates; mutual defection (DD), when a subject defects and an agent defects; subject exploits ($C_HD_A$), when an agent cooperates but the subject defects; and agent exploits ($D_HC_A$), when the subject cooperates but the agent defects. The payoff matrix is shown in Table I.

Here, we use existing agents [7] developed by De Melo *et al.*[7], motivated by claims of Frank *et al.* [25] on how expressions influence cooperation in human-to-agent interactions. Prior studies have demonstrated that the expressions of these agents influence cooperation. In this current study, following the design of De Melo, all agents follow the same strategy to choose their actions (tit for tat) but, display different facial expressions depending on the outcomes in the prisoner dilemma game. We investigate three different patterns of facial displays which we call strong, soft and cooperative as an independent variable (see Table II). A cooperative agent combines positive and negative incentives to make people cooperate. To differentiate the possibly different effects of positive and negative incentives, we divide the cooperative agent policy into a strong agent for a negative incentive and a soft agent for a positive incentive.

*Cooperative agent* This agent expresses positive emotions that reinforce cooperation (positive incentives) and negative emotions that punish noncooperation (negative incentives). It expresses joy in CC condition, remorse in $C_HD_A$ condition, sad in DD condition, and angry in $D_HC_A$ condition;

*Strong agent* This agent expresses emotions that punish noncooperation. It expresses sad in DD condition and angry in $D_HC_A$ condition. Otherwise, it expresses neutral;

*Soft agent* This agent expresses emotions that reinforce cooperative actions. It expresses joy in CC condition and remorse in $C_HD_A$ condition. This is opposed to the strong agent condition.

The experimental conditions are implemented using three appearances as shown in Figure 1. This is to ensure that the effect is due to emotional expression rather than character appearance. Bodies are assigned to conditions randomly, in a counterbalanced design.

## 3.2. Research Hypotheses

Our first hypothesis is that agents' facial expressions will elicit greater affective response in terms of arousal and valence than agents with no emotional expression. In formulating this, we refer the work by Frank, where he argued that expressions of moral emotions induce specific feelings [25,26]. Therefore, we hypothesize that an angry expression after the participant exploits elicits the feeling of guilt and should lead to more arousal and negative valence when compared with a neutral expression [27]. Likewise, joy after mutual cooperation elicits happiness and should lead to more arousal and positive valence than if no emotion were expressed. Remorse after the agent exploited should lead to positive valence with the feeling of relief. Sadness

**Table I.** Payoff matrix for the game.

| | | Agent | |
|---|---|---|---|
| | | Project Green | Project Blue |
| User | Project Green | Agent: 5 pt<br>User: 5 pt | Agent: 7 pt<br>User: 3 pt |
| | Project Blue | Agent: 3 pt<br>User: 7 pt | Agent: 4 pt<br>User: 4 pt |

**Table II.** Experimental conditions.

| | CC | DD | $C_HD_A$ | $D_HC_A$ |
|---|---|---|---|---|
| Strong | Neutral | Sadness | Neutral | Anger |
| Soft | Joy | Neutral | Remorse | Neutral |
| Cooperative | Joy | Sadness | Remorse | Anger |

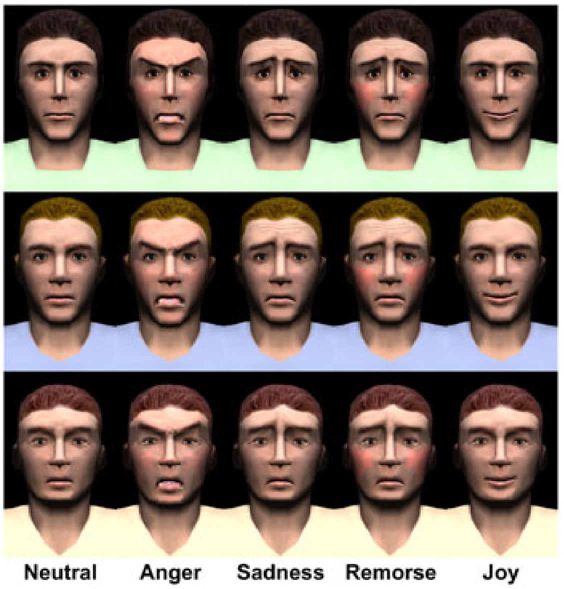



**Figure 1.** Agent bodies and facial displays.

after mutual defection should lead to less negative valence and a feeling of sympathy. We assume that the arousal and valence axes directly link to physiological changes such as EDA and HR [22], where EDA measures arousal and HR measures valence.

H 1.1 CC-Joy will lead to more arousal, positive valence than CC-Neutral
H 1.2 $D_H C_A$-Anger will lead to more arousal, negative valence than $D_H C_A$-Neutral
H 1.3 $C_H D_A$-Remorse will lead to less arousal, positive valence than $C_H D_A$-Neutral
H 1.4 DD-Sad will lead to less arousal, negative valence than DD-Neutral

Our second hypothesis is that the tendency of having an automatically aroused response will be related to cooperative propensity of subjects. The work of Katkin *et al.* [21] indicates that among other things, individuals who have higher arousal of EDA are associated with higher vigilance and better awareness of their own physiological state. Therefore, we split people into two groups on the basis of EDA arousal: highly sensitive group versus less-sensitive group. Accordingly, we expect the highly sensitive people to be affected emotionally by agents' emotional expressions, whereas the less-sensitive people to use emotional expressions as information. To hypothesize on the cooperative behavior of subjects, we follow the emotions as social information (EASI) model of van Kleef *et al.* [26]. They address the dual process of emotional expression in their EASI model. If people use the others' emotions as information, they will consider happiness to signal that the partner is satisfied with the current state of affairs, whereas anger signals that the partner is not satisfied and blames the counterpart for it. Otherwise, if people are catching the others' emotion, then they will tend to cooperate if the agent is happy and defect if the agent is angry. We, thus, expect that highly sensitive people will feel emotions from the agents' emotional expressions and cooperate more with a soft agent than a strong agent. We also expect that less-sensitive people will act strategically on the information retrieved from the agents' emotional signals and cooperate more with a cooperative agent than a soft and a strong agent.

H 2.1 Highly sensitive people will cooperate more with a soft agent and less with a strong agent.
H 2.2 Less-sensitive people will cooperate more with a cooperative agent and less with a soft and a strong agent.

### 3.3. Affective Engagement Measures and Analysis

To assess affective engagement, we measure the affective response of subjects and then observe how affective responses influence motivations and decision making. For the analysis of affective response, we compare results of physiological response with facial expressions to the results from IAPS. Physiological reactions to pictures from IAPS provide a baseline for determining the subjects' emotions during their interactions. As a baseline, many previous researchers use movie, sound, and actor [28] to elicit the affective response of subjects. However, we apply IAPS database as affective stimuli, because IAPS is a standard tool used in emotion-related studies over 15 years. Previously, Lang *et al.* [22] found that visual affective stimuli of pictures based on the IAPS database elicited physiological reactions in the autonomic nervous system, in particular, increased EDA while viewing pleasant and unpleasant pictures. We expect to find similar effects when people view emotional facial expressions in agents.

The procedure for affective response analysis includes feature extraction, outlier removal, and distribution estimation. Regarding analysis, physiological features such as first deceleration of HR were selected. First deceleration indicates the decelerated HR trend from 0 to 3 s. As for EDA features, intensity is used. We transform the EDA intensity with a log transformation; $\log(\mu S + 1)$ [29]. Finally, we average each of the first 6-s window across each round. We check for the presence of outliers with a normality test assuming that all physiological signal distributions follow a Gaussian distribution and remove outliers. Then, we estimate the current physiological distribution that maximizes the probability by assuming a Gaussian mixture model. These data are used to classify arousal and valence.

## 4. EXPERIMENTAL SETUP

Fifty volunteers were recruited from a public website over a 2-month period; each was paid \$20.00 as compensation for their time. A total of 35 men and 15 women participated in the study (average age was 33.4 years). All subjects experienced three agents during the study with the order randomized. Each agent played according to a tit-for-tat strategy and expressed emotions as indicated in Section 3.

Experiments were conducted in a room with constant lighting and temperature, as shown in Figure 2. All testing was performed on a computer. The subjects were seated in front of the monitor, and their facial expressions were captured via a web camera. The experiments took about 1.5 h and proceeded as follows. Upon arrival, the participants received an overview of the study and filled out a pre-questionnaire survey inquiring about their background, demographic information. After that, physiological sensors were attached to the subjects' fingertips. The subjects watched selected pictures from the IAPS projected on the screen. Following this, the participants played the game starting with a tutorial and practice round with the three agents over 25 rounds. They were instructed that their goal is to maximize their credit. Finally, they were asked to answer the post-questionnaire.

We had two distinct measures: physiological data and subjective self-report. Physiological data were acquired using a BIOPAC MP150 (BIOPAC Systems, Inc., Goleta, CA, USA), which included a PhotoPlethysmoGraph (PPG) for HR and an EDA for changes in sweat gland activity. The sensors were placed on the fingertips of one hand; the middle and ring fingers (EDA) and index finger (PPG). The other hand was left unencumbered so to allow the user to make decisions in the game using a mouse. Self-report data included the person perception scale [30]. This scale consists of a pair of words that measures people's impressions of each agent, for example, likable–dislikable, kind–cruel, and friendly–unfriendly.

## 5. EXPERIMENTAL RESULT

### 5.1. Manipulation Check with International Affective Picture System

To ground the study, we did a manipulation check with IAPS. We selected 36 pictures from IAPS: 12 pictures labelled 'pleasant', 12 'neutral', and 12 'unpleasant'. We used pleasant pictures, characterized by a valence rating of 7.8 and an arousal of 5.3 on the basis of a self-report scale

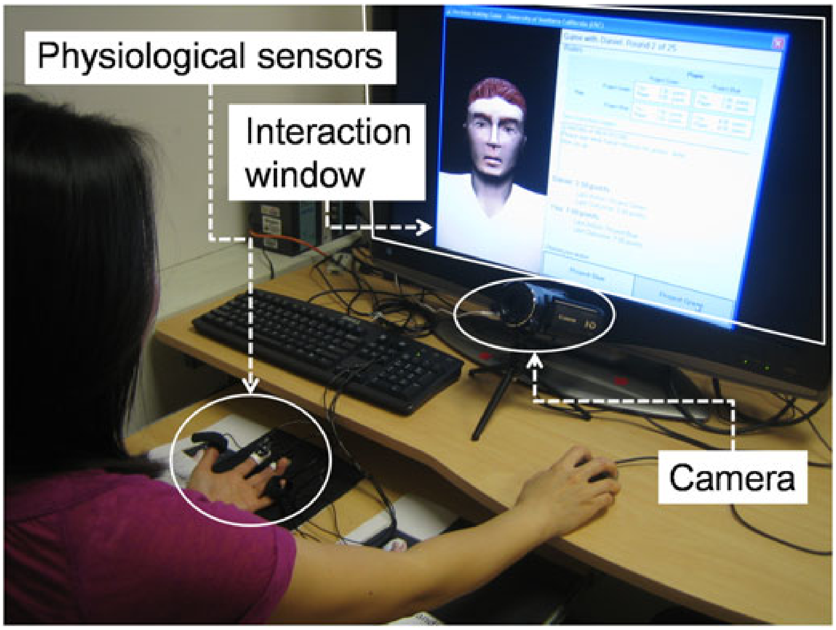



**Figure 2.** Experimental setup.

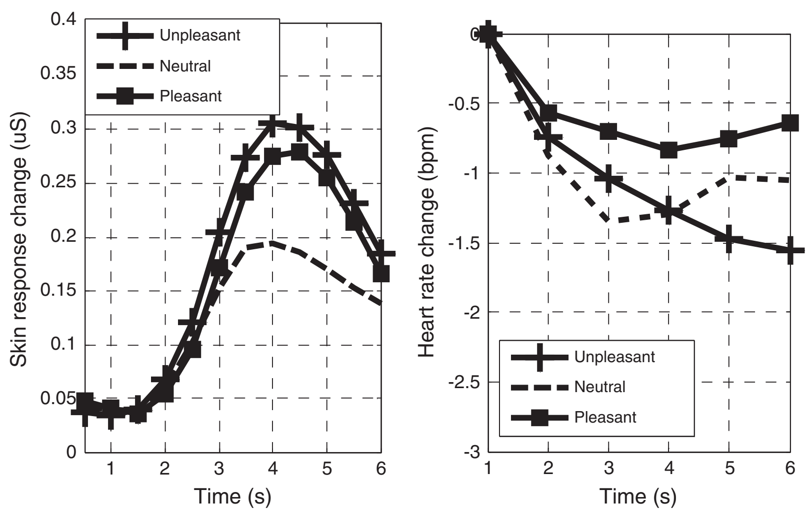


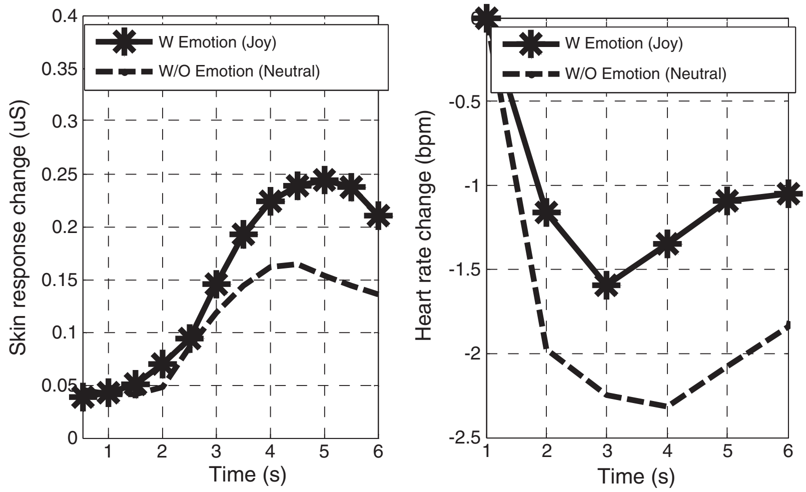

**Figure 3.** Six-second trend of electrodermal activity (left) and heart rate (right).

of 1 to 10; 2.4 valence and 6.2 arousal for negative pictures. These pictures were used to evoke positive, negative, and neutral emotions.

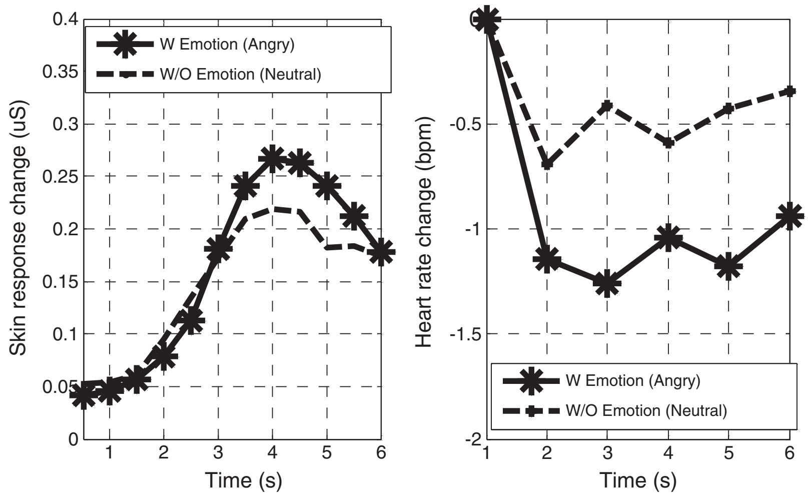
We collected the physiological data of EDA and HR while the subjects watched the selected IAPS pictures. We analyzed the 6-s trend after stimulus onset and checked significant differences with repeated measure of analysis of variance. As shown in Figure 3, we observed significantly increased EDA intensity for pleasant and unpleasant pictures when compared with neutral pictures ($F(2,1128) = 5.438$, $p = 0.004$). For HR, we observed a trend for large first deceleration on HR with unpleasant pictures, but it was not significant. However, observed patterns were similar to the results in previous literature about the IAPS manipulation check [22]: Previous studies reported a largely decreasing HR when viewing unpleasant pictures compared with pleasant ones. Therefore, we concluded that IAPS could be used as a ground truth or reference to analyze emotions in decision-making tasks.

## 5.2. Effect of Facial Expressions on Physiological Affective Responses

We explored the effect of facial expressions on physiological affective responses. As in the IAPS manipulation check, we analyzed EDA and HR for the 6-s window following <outcome, expression> pairs: CC-Joy, agents expressed joy when subjects cooperated and agents cooperated; $C_HD_A$-Remorse, agents expressed remorse when subjects cooperated and agents defected; $D_HC_A$-Angry, agents expressed anger when subjects defected and agents cooperated; and DD-Sad, agents expressed sadness when




(a) CC-Joy vs. CC-Neutral




(b) $D_HC_A$-Angry vs $D_HC_A$-Neutral

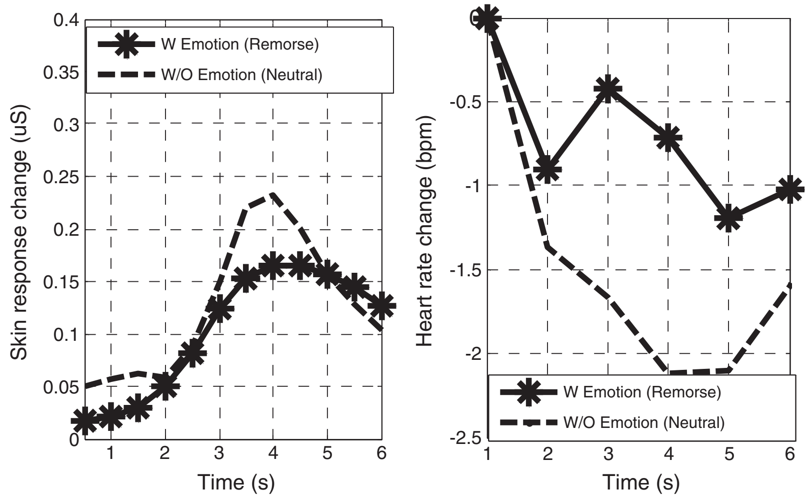
**Figure 4.** Six-second trend of electrodermal activity (left) and heart rate (right).

subjects defected and agents defected. All data were an average over the 25 rounds across participants.

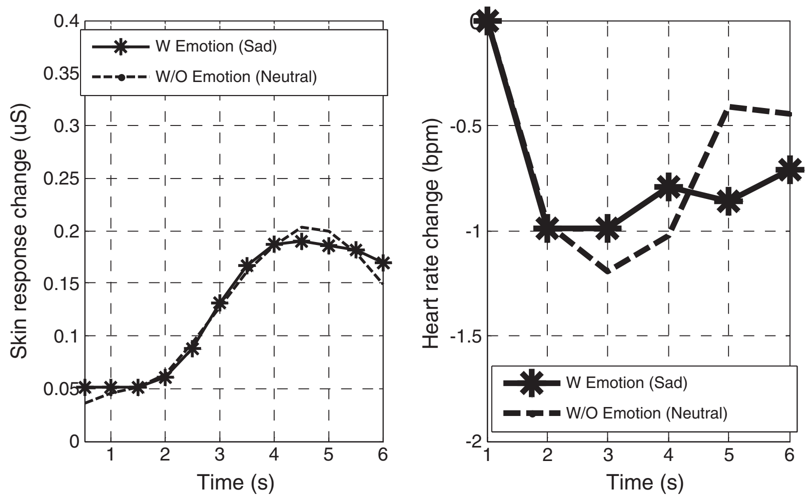
As shown in Figure 4, we observed differences in EDA response to emotion expressions, when compared with the no-emotion case. For EDA, it was clear that the $D_HC_A$-Angry and CC-Joy evoked more arousal than $D_HC_A$-Neutral and CC-Neutral, in Figure 4(a) and (b). In contrast, the $C_HD_A$-Remorse led to less arousal than the $C_HD_A$-Neutral in Figure 4(c). Finally, the DD-Sad showed no significant differences in Figure 4(d).

These results indicated that CC-Joy and $D_HC_A$-Angry strongly affected subjects' responses and were experienced as stimulating when compared with neutral expressions. For HR, we observed reduced first deceleration of HR in CC-Joy and $C_HD_A$-Remorse, which indicated that both cases evoked positive valence compared with the neutral case. In contrast, the $C_HD_A$-Angry evoked negative valence compared with the $C_HD_A$-Neutral. From these results, we found that hypothesis H1.1, H 1.2, and H 1.3 were confirmed, but hypothesis H 1.4 was not supported. Apparently, sadness in the context of mutual defection does not add to the subjects' emotional reactions.

The result for HR and EDA of CC-Joy and $D_HC_A$-Angry matched the pattern to the IAPS result. For example, the pattern of reduced HR deceleration and increased EDA intensity in CC-Joy was similar to the result for pleasant pictures with IAPS. In addition, the results for $D_HC_A$-Angry were also similar to the results for unpleasant pictures with IAPS. Other researchers have also found small first deceleration of HR when people experienced positive stimuli (e.g., fair offers) and large first deceleration of HR when people experienced negative stimuli (e.g., unfair offers) [16,17]. Thus, we infer that subjects responded emotionally to emotional expressions of agents.




(c) $C_HD_A$-Remorse vs. $C_HD_A$-Neutral




(d) DD-Sad vs. DD-Neutral

**Figure 4.** *Continued.*

### 5.3. Association of Cooperative Behavior and Physiological Affective Response

We explored whether physiological response was associated with cooperative behavior. To understand cooperative behavior, we calculated the cooperation rate, that is, the number of times a subject cooperated in a game divided by the number of rounds. To understand the relation between physiological responses and behavior, we divided the subjects into two groups according to how they responded to emotional stimuli. We used EDA response in IAPS to distinguish physiologically highly sensitive subjects and less-sensitive subjects. For this classification, we applied data fitting to a Gaussian mixture model of EDA intensity (log-likelihood = 35.241) and clustered for the fitted mixture distribution.

As shown in Figure 6 and Table III, we applied analysis of variance with repeated measures to analyze cooperation rate. There was a main effect on agent type ($F(2, 96) = 12.86$, $p < .001$) and interaction between agent and sensitivity ($F(2, 96) = 26.7$, $p<.001$) in terms of cooperative rate. Highly sensitive subjects cooperated the most with the soft agent and the least with the strong agent. Less-sensitive subjects cooperated the most with the cooperative agent and the least with the soft agent.

These results show that hypothesis H 2.1 for highly sensitive subjects was met. Thus, we infer that highly sensitive subjects feel positively (or negatively), and this led people to cooperate more with the soft agent (or cooperate less with the strong agent). In addition, hypothesis H 2.2 was confirmed from the results. For the less-sensitive people, we observed that they cooperated more with a cooperative agents compared with the other agents. We will discuss this issue in Section 5.4.

We also analyzed the self-report measure with person perception score of highly sensitive and less-sensitive subjects, as shown in Table IV. The results indicated that highly sensitive subjects had a positive perception of the soft agents but a negative perception of the strong agents. On the other hand, less-sensitive subjects did not show significant differences between the three agents.

### 5.4. Discussion and Implication

In this work, we explored the question of whether facial expressions gave off emotional or informational signals. Our study was designed to assess whether people exhibited physiological responses to emotional facial expressions. We observed the effect of facial expressions on

**Table III.** Descriptive statistics of cooperation rate (0 = not cooperative, 1 = most cooperative).

| | Less sensitive | | Highly sensitive | | |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Significance |
| Strong | 0.406 | 0.045 | 0.235 | 0.057 | $p = 0.000^*$ |
| Cooperative | 0.520 | 0.058 | 0.320 | 0.038 | $p = 0.000^*$ |
| Soft | 0.309 | 0.047 | 0.382 | 0.060 | $p = 0.023^*$ |

$^*p < 0.05$.

**Table IV.** Person perception (−3 = mostly negative attributes, +3 = mostly positive attributes).

| | Less sensitive | | | Highly sensitive | | | |
|---|---|---|---|---|---|---|---|
| | St | Co | So | St | Co | So | Significance |
| Friendly | 1.4 | 0.6 | 1.3 | 0.0 | 0.2 | 1.0 | $p(l) = 0.422$<br>$p(h) = 0.042^*$ |
| Warm | 1.0 | 0.6 | 1.2 | −0.2 | 0.2 | 0.8 | $p(l) = 0.422$<br>$p(h) = 0.037^*$ |
| Involved | 1.4 | 0.4 | 1.2 | 1.4 | 0.8 | 0.2 | $p(l) = 0.559$<br>$p(h) = 0.035^*$ |
| Pleasant | 1.1 | 0.7 | 1.1 | −0.3 | 0.0 | 0.8 | $p(l) = 0.620$<br>$p(h) = 0.012^*$ |
| Threatening | 0.2 | 0.4 | −0.4 | 0.4 | 0.0 | −1.0 | $p(l) = 0.448$<br>$p(h) = 0.000^*$ |
| Sympathetic | 1.0 | 0.4 | 0.7 | −0.5 | 0.0 | 1.0 | $p(l) = 0.560$<br>$p(h) = 0.002^*$ |
| Arrogant | 0.0 | −0.3 | −0.2 | 0.5 | 0.0 | −1.0 | $p(l) = 0.788$<br>$p(h) = 0.004^*$ |
| Strong | 1.2 | 1.0 | 0.4 | 0.6 | 0.6 | −0.2 | $p(l) = 0.346$<br>$p(h) = 0.039^*$ |

St, strong agents; Co, cooperative agents; So, soft agents; $p$(l), significant difference of less-sensitive group; $p$(h), significant difference of highly sensitive group.
$^*p < 0.05$.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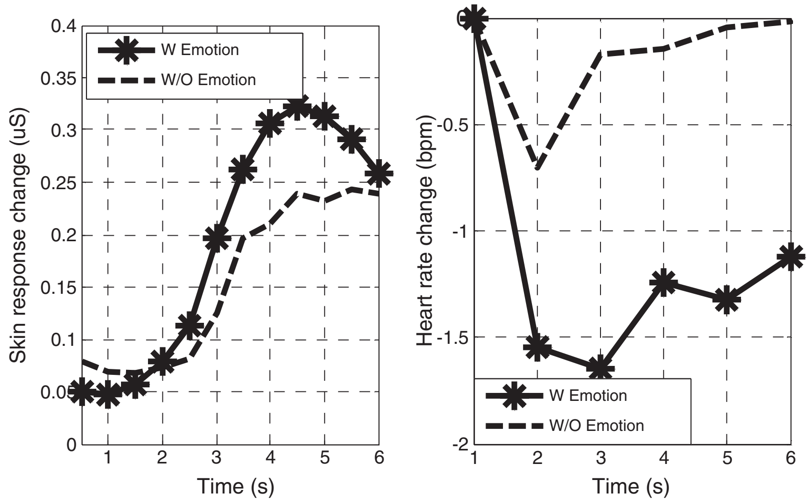
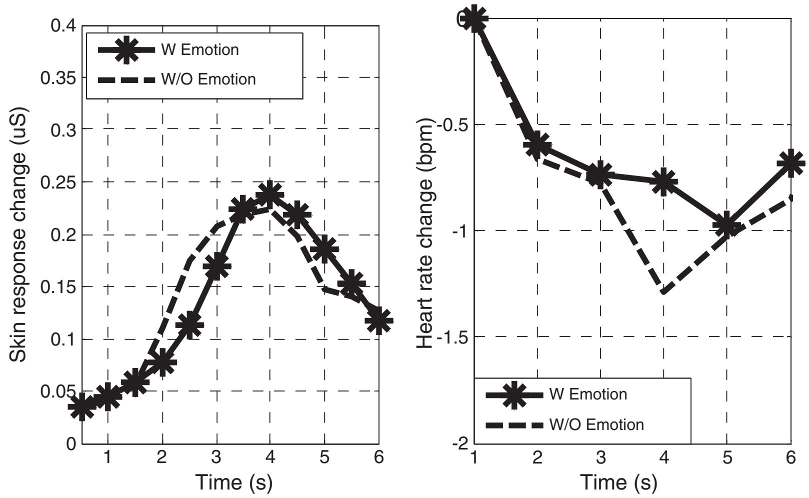
physiological responses (Figure 4). By classifying subjects on the basis of their physiological sensitivity on a previous emotional task (e.g., IAPS), we found that it also predicts cooperative behavior with expressive agents (Figure 6). However, the differences of cooperative patterns based on physiological sensitivity require some explanation.

One possible explanation is seen in Figure 5. This figure shows that highly sensitive people perceived agents' facial expressions as emotional signals. The results demonstrate that strong agents' angry expressions evoke negative emotions of the highly sensitive people (Figure 5(a)), which cause them to disengage and cooperate least with the strong agents (Figure 6(b)). Similarly, the soft agents, expressing joy, evoke positive emotions in highly sensitive people (Figure 4(a)), which cause them to cooperate most with the soft agents. We further found that highly sensitive people perceive the soft agents more positively than the strong agents (Table IV). Therefore, it seems that highly sensitive people decide their action on the basis of their emotions and impressions toward the agents.

In contrast, for less-sensitive people, we found that they cooperated most with the cooperative agents, less with the strong agent, and least with the soft agents (Figure 6). We interpret the result on the basis of the EASI model [26]. The model suggests that when people use emotion as information, they do so strategically. Thus, when they face an angry (strong) counterpart, they concede to it or risk nonagreement. In our case, people cooperate with the strong agent, because they interpret it to be blaming the participant for insufficient cooperation. Thus, they feel compelled to cooperate themselves or risk noncooperation from the agent. On the other hand, when faced with a happy (or soft) counterpart, people will tend to exploit it. In our case, because the soft agent only shows positive

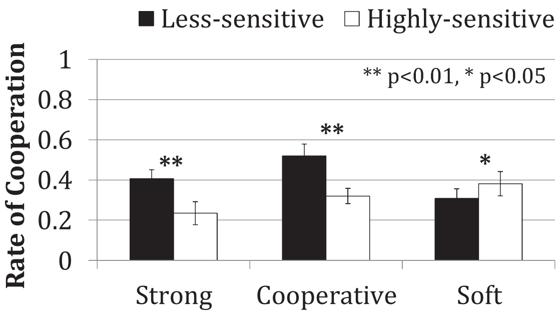



(a) Highly-sensitive group

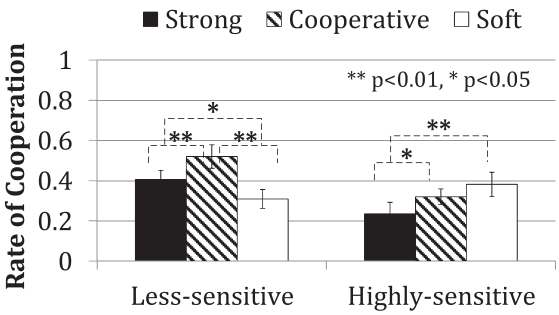



(b) Less-sensitive group

**Figure 5.** Six-second trend of electrodermal activity (left) and heart rate (right) of $C_H D_A$-Angry.




(a) Type of agents




(b) Sensitivity level

**Figure 6.** Cooperation rate.

emotions, despite noncooperation from the participants, people feel tempted to continue exploiting it. For the cooperative agent, it is clear that the agent wants to cooperate; in which case, less-sensitive subjects will also cooperate. In summary, our results lend supporting evidence of dual processes in EASI model; affective reaction from highly sensitive people and inferential process from less-sensitive people. Additionally, the results show that each process leads to different cooperative behavior.

This work is important to develop social agents for several reasons. First, it adds further evidence that people can react to emotions displayed by agents in the same way as emotions displayed by people. The paper also clarifies which emotions promote cooperation and which ones do not. Finally, the study clarifies that there are, at least, two types of users—highly sensitive and less sensitive—which react very distinctively to emotion displays. Physiological measures can be used to identify which type of user the agent is interacting with and, thus, adapt its displays appropriately to achieve an interaction objective (e.g., promote cooperation). Inversely, this work suggests how we can infer about the user's physiological state from his or her cooperative behavior.

## 6. CONCLUSION AND FUTURE WORK

We explore people's affective engagement when interacting with socially expressive embodied agents with the use of a decision-making game. Overall, the results emphasize that emotion expressions in agents affect people emotionally. People who are engaged affectively to emotional signals cooperate more or less if they feel that this agent is either positive or negative to them. In addition, people who are not engaged affectively cooperate more with the agents that send signals to cooperate on the basis of inferential process.

There are several issues to be considered in future studies. We need to consider that the same emotional expressions can have different effects according to context. Thus, for future studies, we will explore the effect of context according to the type of agents' facial expressions. In addition, we may apply these results to build a more socially interactive agent. These observations emphasize the need to understand the processes of subjects' behaviors during social interactions.

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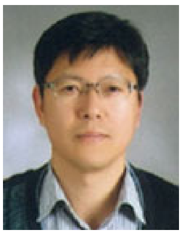

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