The influence of emotional expressions of an industrial robot on human collaborative decision-making

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***Abstract*—In recent years, robots have been equipped with the ability to express emotions and have begun building social relationships with people. However, the significance and effectiveness of incorporating emotion in industrial robots, which have a strong instrumental nature, is not fully understood. We investigated how emotional expressions of an industrial robot influence human collaborative decision-making. The participants (n=52), in a laboratory experiment, engaged in a dessert survival task with an arm robot in a 2 (emotion expression: present vs. absent) $\times$ 2 (competence: high vs. low) between-participants study. Emotion was expressed using color through a LED strip of lights - e.g., anger was conveyed by flashing red. The results showed that emotion expression and competence did not influence the final agreement and, in fact, emotion expressions made the interaction longer, emphasizing the difficulty in communicating emotion and the reason for those expressions. We discuss lessons learnt and provide insight on improving the value of emotion expression in industrial robots.**

***Index Terms*—industrial robot, emotion expression, decision-making, collaboration, assistance**

I. Introduction

Since the Stone Age, humans have extended their physical capabilities with tools and machines, and recently they extended their intellectual capabilities with computers to reduce the cost of achieving their goals. However, with the development of artificial intelligence, machines have become capable of goal-directed tasks [45], and the development of actuators and materials has enabled them to show sophisticated emotion expressions, i.e., tools are becoming more human-like. Emotion, especially interpersonal emotion, is an evolutionary acquired and embedded function for regulating human relationships [6], [8]. In recent years, many robots have been equipped with the ability to express emotions and have begun to build social relationships with people (for a review see [10], [53]). However, the significance and effectiveness of incorporating emotion, the basis of human social behavior, in industrial robots, which have a strong instrumental nature, has not been fully studied [13]. In the present study, we investigate how emotional expressions of an industrial robot influence human cooperative decision-making.

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It has long been proposed that emotions influence the observer's affect, cognition, and behavior, usually referred to as the interpersonal effects of emotion [6], [8]. From an evolutionary perspective, interpersonal effects can be divided into competition and cooperation [6]. When two genetically different organisms live together, there is always a conflict of interests as well as increase in profit through collaboration, thus the problem that should be solved by two parties is sometimes modeled as a zero-sum game and sometimes as a non-zero-sum game. Emotion expressions are considered to have evolved to solve these games without physical confrontation. For example, in simple distributional tasks, often modeled as ultimatum or dictator games, it is known that the recipient's negative emotion expressions before the proposer's decision elicits higher offers from the proposer [7], [28], [48], [54], [56], which in turn contributes to a fairer distribution of the resources. Research has shown that in dilemma situations where cooperative and competitive decisions are available, often modeled as the prisoner's dilemma, expressing regret after a betrayal is more likely to lead to mutual cooperation than expressing a smile [35], [36], contributing to avoid exploitation and building cooperative relationships.

Emotion expressions are able to shape behavior of observers because the emotion expressions trigger observers' affective reactions (i.e., reciprocal and complementary emotions) and/or inferential processes [21], [22], [24]. Known as appraisal theory, emotions in an individual emerge reflecting a positive or negative evaluation of an event or situation relative to their concerns or goals [37], then are displayed as emotion expressions. The observer decodes the observed emotions through an inferential process called reverse appraisal, which allows the observer to infer the goal, appraisals and beliefs of the person expressing emotion [35], [59].

Anger arises when an individual's goals are thwarted and they blame someone else for it. Anger not only generates reciprocal anger and complementary fear but also triggers inferences in the observer. Anger in negotiation encodes limits

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[7], [23], [27], power [20], [25], toughness [49], social motives [7], [54], and preferences [40]. The observer of anger concedes rationally by inferring that the other has high limits, high power, or is tough. For this reason, the expression of anger can be counterproductive when faced with powerful counterparts and, rather, it can be a better strategy to elicit guilt from the counterpart by expressing sadness or disappointment [28], [48].

Joy arises when things are going in line with one's goals [50]. Thus, the observer does not change their behavior because they interpret that the other is satisfied with the situation. Moreover, the expression of joy in negotiation can lead to the inference of generosity and low limits, leading to exploitation by the observer [23]. However, in a distribution task such as in an ultimatum game, the proposer's joy can induce reciprocal joy as well as inference of high power (better alternatives) in the responder, forcing the responder to accept an unfair offer [38], [41].

Using game theoretical situations, studies showed that the effects of robots' emotion expressions are similar to human-human interaction, suggesting that facial expressions contribute to correct human-robot inequality [54], [56] and to construct cooperative relationships [34]–[36], [55]. However, the human-robot relationship is more collaborative and assistive than competitive. Robots, including software agents, are tools that assist people in physical and mental labor, unless someone uses them for exploitative purposes. Robot makers and sellers consider profit, but the robots themselves do not consider their own profit. Therefore, robots and people are not essentially characterized as having a competitive or cooperative relationship. However, due to anthropomorphic characteristics of robots, people sometimes attribute mental states to them and treat them as colleagues even if the robot is a manipulator in a factory [47]. Hentout et al.'s literature review suggests that there are challenges related to building social relationships between humans and industrial robots in problem-solving and coordinating work [13].

Numerous studies have shown that emotion expressions of agents, including physical robots and software agents, influence human decision making in assistive situations, such as tutoring [29] (for a meta analysis, see [10]), healthcare [3], [5] (for a review see [52] and note that no clear consensus exist for emotional agents triggering behavior change in people while likeability and believably are rated higher when agents show emotion expressions), and recognition tasks [46]. However, the influence of the robot's emotion expressions on decision-making when a person and a robot are pursuing a single goal in a team is still unclear.

In the present study, we considered a situation in which a human and a robot collaborate to solve a problem: the desert survival task [26]. The desert survival task has been used in human-robot and human-agent joint problem solving and decision making studies [4], [16], [17], [30], [39], [42]. Nass et al. showed that participants followed computer's suggestions, sent by text, more when they were instructed that they were interdependent with the computer [39]. Chidambaram et al. showed that participants complied with the humanoid robot's suggestions significantly more when it used nonverbal cues than when it did not use these cues and that bodily cues were more effective in persuading participants than vocal cues were [4]. Khan and Sutcliffe showed that participants followed vocal suggestions more from attractive human-like virtual agents than unattractive agents [16]. Li et al. showed that participants who watched the video of the human-robot desert survival task were less attracted and judged the robot to be less trustworthy, less socially attractive and less affectionate when the robot was dominant, providing a confident opinion, compared to when it was submissive [30]. Pütten et al. showed that dominant nonverbal behavior shown by a virtual agent was more successful than submissive nonverbal behavior to persuade seniors, while dominant behavior did not lead to stronger persuasive effects for young adults [42].

We used full color LEDs to express the robot's emotion expressions, instead of attaching an expression device like a human face to an industrial arm robot. It has been suggested that there is an association between color and emotion. Many studies have shown that emotional expression through color can lead to perceptions of emotional states in abstract shaped robots [14], [57] and humanoid robots [15], [18], including attractiveness and hostility [51], and shape economic decision making in dilemma situations [55]. However, Pütten et al. showed that expressing emotion with color is less effective for emotional experience and self-disclosure than human-like nonverbal behavior represented by movement of head, arms, and torso [44], whereas Löffler et al. showed that the effectiveness of the modality combination depends on the type of emotion, e.g., anger can be effectively communicated by color [31].

The robot's competence could also be a factor in determining whether people follow the robot's suggestions and, furthermore, its effect may interact with the effect of emotion. There is research indicating that people usually follow the opinion of more competent (prestigious) people [58]. Since anger can elicit concessions from counterparts and anger encodes dominance [21] - a leadership quality alongside competence [58] - it is possible that there is a synergistic effect between emotion, especially anger, and the competence of robots. For this reason, we considered robot's competence as a second factor in the experiment.

In the present study, we investigated the effect of emotion expressions and competence in an industrial robot (COBBOTA, a DENSO arm robot, Fig 1a) on human decision making in the desert survival task.

II. Methods

A. Participants and ethics

All participants were recruited in an online participant pool in Gifu University. To estimate the sample size, we did the power calculations using G*Power. Based on earlier work [4], we predicted a medium to large effect size ($\eta_p^2 = .2$) in terms of the agreement. For a two-factor (emotion expression [present, absent] $\times$ competence [high, low]), between-participant factorial design, $\alpha = .05$, and a statistical power of .95, the recommended total sample size was 55 participants. We aimed to recruit 56 participants (14 per condition). A total of 54 (36 males; $M_{age} = 21.7, SD_{age} = 3.2$, 18 females; $M_{age} = 23.5, SD_{age} = 8.1$) university students and staff participated in the study. We excluded 2 participants who did not complete the task because of a malfunction with the robot movement. Thus, we analyzed 52 samples.

All experimental methods were approved by the Medical Review Board of Gifu University Graduate School of Medicine (IRB ID#2018-159).

B. Materials

1) Desert survival task: The desert survival task is a task in which groups of people prioritize 15 items to survive in the desert [26]. The 15 items used in the present study and their optimal priorities, provided by Alonzo W. Pond (a survival expert), were as follows: 1st, cosmetic mirror; 2nd, top coat; 3rd, 1 quart of water; 4th, flashlight; 5th, parachute (red and white); 6th, jackknife; 7th, plastic raincoat; 8th, pistol (loaded); 9th, a pair of sunglasses; 10th, compress kit with gauze; 11th, magnetic compass; 12th, map of the area; 13th, a book entitled “Edible Animals of the Desert”; 14th, 2 quarts of Vodka; and 15th, salt tablets. Of the 15 items, there are items that, at first glance, may seem unnecessary for desert survival, such as the cosmetic mirror and top coat usually worn in cold weather, with individual priorities varying according to knowledge and personal values. For this reason, the desert survival task is a task that requires an exchange of information in order to reach agreement on the prioritization of items among several people.

We modified the desert survival task in which a participant and a robot jointly determine five items for survival in the desert from a list of 15 items through a touch panel interface in which two parties alternately express their choice 1c. Functions in the interface allow players to indicate their acceptance or rejection of their counterparts’ proposals. In the interface, the picture of 15 items were displayed. The background of the item changed to white or black each time it was touched, indicating it was selected or deselected, respectively. Each player was asked to select one item, even if it had been already selected, within their turn, and was also allowed to deselect one item if necessary. If a player selected an item whose background was white indicating that the item was already being selected, the white area of the background expanded momentarily, providing feedback to the player that the selection had been overwritten. In each given turn, only one item was allowed to be selected (mandatory), and one item was allowed to be deselected (optional). When the “Propose” button was pressed, the “Propose” button disappeared and the picture of the item vertically inverted (correctly shown to the counterpart), clearly indicating that the turn has been moved to the counterpart. The maximum number of turns was 30, i.e., 15 turns for each player. The first turn was given to the robot. Participants started the desert survival task by pressing the “Start” button. When there were five selected items, the “Agree” button appeared on the interface, and if the players agreed with the five items, they could press the ‘button. Pressing the “Agree” button terminated the task, but the robot never pressed this button.

2) Robot: We used a six degrees of freedom arm collaborative robot COBOTTA by Denso Robotics, Inc. shown in Fig 1a. The robot weighs approximately 4 kg, has a maximum payload of 0.5 kg, and a maximum reach of 342.5 mm. The robot has one gripper which can grab a 30 mm object. We put a stylus pen in the grip so that the robot could use the touchscreen. A LED strip light was attached on the arm near gripper to show the emotional states of the robot.

3) Robot’s priority: The robot selected items according to its own priority. The priority of the items was determined by the competence factor. At the high competence level, the five items ranked first, second, third, sixth, and seventh in the optimal priority order. At the low competence level, the five items ranked seventh, eighth, thirteenth, fourteenth, and fifteenth in the optimal priority order. The remaining items were ordered according to their original priority.

The robot basically selected from its highest priority items. If the participant deselected the robot’s proposed item, it selected the item again up to two times. See Supplementary Methods A for details on the algorithm.

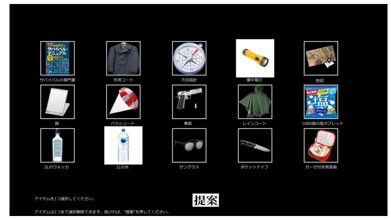
4) Emotion expression of robot: For the emotion condition, the robot expressed anger or joy with the dynamic coloring of the LED strip light using the emotion expression model proposed by Terada et al. [57]. Anger was expressed by Hue = 1 (FF0400, ■), blinking cycle = 312ms, and luminance change = 14% and joy was expressed by Hue = 108 (32FF00, ■), blinking cycle = 2601ms, and luminance change = 50%. The luminance change ratio represents the percentage of the square wave of 1/2 cycle of the blinking cycle that is replaced by a cosine wave. The larger the ratio of the luminance change, the slower the luminance increase and decrease within the cycle. See Fig. 1d and 1e for waveform and color. See also Supplementary Movies 1 and 2.

An online validation study was conducted to investigate whether these emotions were recognized as expected. We recruited a separate sample of 49 participants (40 males; $M_{age} = 45.7$, $SD_{age} = 8.9$, 9 females; $M_{age} = 44.4$, $SD_{age} = 9.9$) from the Yahoo! Japan Crowdsourcing online pool. We tested a total of four expressions including neutral (no expression) and Hue = 37 (FF9D00, ■), blinking cycle = 1124ms, and luminance change = 35% [1], in addition to the above two color luminance pattern, Hue = 1 and Hue = 108. To investigate the context-dependence of emotion recognition, we showed emotion expression with and without task context. The latter was implemented by the presence of a particular object and the pose of the arm pointing at that object. Thus, we created a total of 8 videos (4 emotions $\times$ 2 [context present vs. absent]). Participants were asked to watch eight short movies (in counterbalanced order), and to rate, on 7-point Likert scales, how likely the robot in the movie expressed

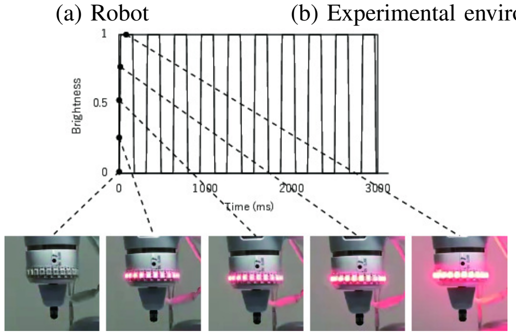
[1] In [57], Hue = 37 was labelled as joy and Hue = 108 was labelled as trust. However, to explore a suitable expression, Hue = 108 was used as a candidate for joy.

(a) Robot

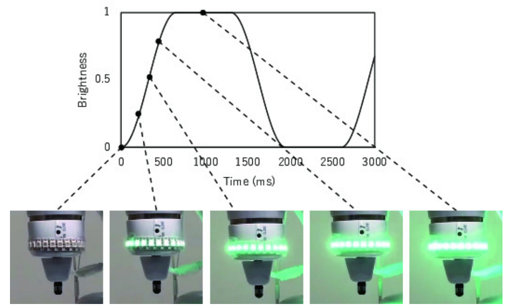
(b) Experimental environment



(c) Desert survival task interface



(d) Anger



(e) Joy

Fig. 1: Methods

the following five emotions: joy, sadness, anger, regret, and neutral. A repeated one-way ANOVA was performed on the emotion ratings for each emotion video, and a Bonferroni-corrected comparison revealed that the neutral expression was perceived as neutral and Hue = 1 as anger. However, Hue = 37 was confused with neutral without context, and with sadness when context was added. Hue = 108 was perceived as joy and confused with neutral, but not confused with other emotions especially sadness. Thus, we used Hue = 108 as an emotion representing joy. See Supplementary Methods B for more details.

The robot emotion expressions were chosen according to the participant's decisions. Anger was expressed when the participant deselected the item the robot selected in the previous turn. The robot expressed joy when the participant did not deselect the item the robot selected in the previous turn. In the no emotion condition, the robot did not express any emotion. For more details on the robot's emotion expression algorithm, see Supplementary Methods A.

C. Procedure and incentive

Upon arrival at the laboratory, participants were seated in a curtain partitioned area in front of a computer, which displayed the experimental instructions, and the robot. After signing a consent form, participants were allowed to start the desert survival task with the robot (See Fig1b), followed by a post-questionnaire.

The participants were paid 1,000 JPY (∼\$9 USD) for participating in the experiment.

D. Measures and analysis

1) Manipulation checks: As a manipulation check for the emotion expression factor, participants were asked on a 7-point Likert scale (1 = never perceived to 7 = strongly perceived) how much joy, sadness, anger, regret, and neutral they perceived from each of the two luminance pattern expressed by the robot. We used the prestige scale [42] in the subjective measures described below as a manipulation check for the competence factor.

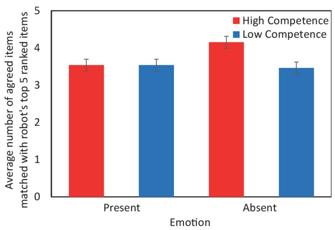
2) Objective measures: We recorded which item was selected and deselected by the participants in each turn. From these records, we measured how many items in the final agreement matched the robot's preferences. To assess the quality of the interaction, we counted the number of turns taken to reach agreement, and how many of the robot's top 5 items were selected in each turn. In addition, to assess how often participants rejected the robot's recommendation, the number of times the participants deselected the item the robot selected in the previous turn were counted and their percentage of the total turns was calculated.

Video recordings were made to record the details of the interactions. See Supplementary Movies for videos of all conditions.

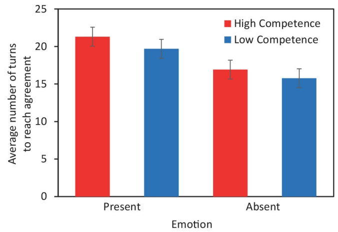
3) Subjective measures: Building on prior work, we used modified scales to measure robot's dominance (6 items) [42], prestige (5 items) [42], cooperativeness (5 items) [16], trustworthiness (5 items) [1], [43], presence (4 items) [32], usability (4 items) [2], workload (5 items) [11], and reliability (5 items) [33] on a 7-point Likert scale with multiple questions for each scale. The full list of items is shown in the Supplementary Methods C. The Cronbach's α for each scale is shown in Table I.

4) Analysis: Two-way and repeated-measures ANOVAs were performed to examine the effects of emotion and competence on both objective and subjective measures. All statements of significance were based on a probability of $p \leq .05$.

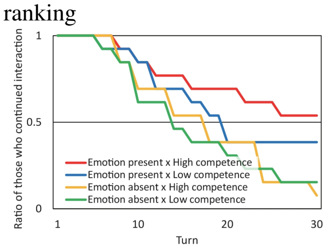
To investigate whether robot dominance, prestige, cooperativeness, trustworthiness, presence, usability, reliability, and workload predicted the number of final agreed items and num-



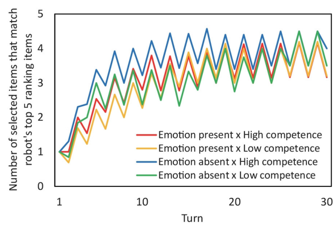
(a) Number of final agreed items matched with the robot's top 5 ranking



(b) Number of turns to reach agreement



(c) Ratio of participants who continued interaction



(d) Number of selected items matched with the robot's top 5 ranking

Fig. 2: Results. Error bars show the standard errors.

ber of turns to reach an agreement, we performed a stepwise regression analysis using the scale values in all conditions as independent variables. The final model was selected based on the Akaike information criterion (AIC).

III. Results

1) Manipulation checks: The repeated ANOVA showed that participants perceived the robot's expression of anger as anger ($M = 5.9, SD = 0.9$) and this was significantly higher than joy ($M = 1.3, SD = 0.9, p < .001$), sadness ($M = 4.3, SD = 1.8, p = .002$), regret ($M = 2.0, SD = 1.5, p < .001$), and neutral ($M = 2.8, SD = 2.0, p < .001$). Participants perceived the robot's expression of joy as joy ($M = 6.0, SD = 0.9$) and this was significantly higher than sadness ($M = 1.3, SD = 0.8, p < .001$), anger ($M = 1.3, SD = 0.9, p < .001$), regret ($M = 1.4, SD = 0.9, p < .001$), and neutral ($M = 2.6, SD = 1.8, p < .001$). Thus, anger and joy were perceived as expected. See Supplementary Methods D for more details.

A two-way ANOVA on the prestige scale showed no main effect of the competence factor ($F(1, 48) = 0.11, p = .74, \eta_p^2 = .002$), indicating that our method did not properly manipulate the robot's competence.

2) Objective measures: Table I shows descriptive statistics and two-way ANOVA statistics for the objective measures. Fig 2 shows the number of final agreed items, number of turns to reach agreement, number of selected items matched with the robot's top 5 ranking, and participant's deselection ratio. The analysis showed that the number of final agreed items was not affected by the presence or absence of emotion expressions or competence, that the number of turns to reach agreement was higher when the robot showed emotion, and that the participant's rejection rate did not differ among all conditions.

To understand more about the dynamics of the interaction as it unfolded in time, we conducted a more detailed analysis. Fig. 2c shows the ratio of participants who continued the interaction (i.e., failed to reach agreement) plotted against turn. At least five interactions were made by all of the participants and 75% of the participants continued for ten turns. Therefore, we focused on the first 10 turns and compared across conditions how the number of items matched the robot's top five ranked items as the interaction proceeded. Three-way repeated-measures ANOVA with turn as a repeated factor for 39 participants who reached 10 turns showed that there were main effects of turns, $F(9, 315) = 122.60, p < .001, \eta_p^2 = .78$, and interactions between turns and emotion, $F(9, 315) = 3.36, p < .001, \eta_p^2 = .09$, and turn and competence, $F(9, 315) = 2.50, p = .01, \eta_p^2 = .07$, respectively, indicating that the number of matched items increased as the interaction progressed. Throughout the 10 turns, there was no interaction between emotion and competence, $F(1, 35) = .52, p = .48, \eta_p^2 = .015$, but there was a main effect of emotion, $F(1, 35) = 8.82, p = .005, \eta_p^2 = .201$, and the number of agreed items was larger when the robot did not express emotions, $M = 2.56, SD = .12$, than when it did, $M = 2.08, SD = .11$. There was also a main effect of competence, $F(1, 35) = 10.89, p = .002, \eta_p^2 = .237$, and the number of agreed items was larger for high, $M = 2.59, SD = .11$, than for low competence, $M = 2.06, SD = 12$.

3) Subjective measures: The analysis shows that, for all scales, there were no significant interactions between emotion and competence and no main effect of emotion or competence. Details are shown in Table I.

4) Exploratory analysis: Table II shows the results of the stepwise multiple regression analysis. The final models to predict the number of agreed items, $F(2, 49) = 11.54$, $p < .001$, $R^2 = .32$, $R^2_{Adj} = .29$, and the turns to reach an agreement, $F(1, 50) = 19.17$, $p < .001$, $R^2 = .28$, $R^2_{Adj} = .26$, are all significant.

IV. Discussion

In this paper we investigated the effect of emotion expressions of an industrial robot on human decision making in the desert survival task. The emotion expressions were meant to reinforce the robot's recommendations with negative (anger) and positive (joy) signals and, overall, help users have a better understanding of the robot's behavior and intentions. However, our results indicated that participants took longer to reach agreement when emotion was expressed, even though there was no statistical difference in the quality of the final solution between the emotion and neutral conditions. This may have happened because emotions were not sufficient to provide a justification for the robot's recommendations. For instance, whereas it might have been clear that an angry robot did not appreciate the participant deselecting its recommendation, it might have not been clear why the recommendation was made in the first place, i.e., what was the value of the recommended item to survival in the desert. Prior work indicates that justified recommendations can be effective in improving the solution

TABLE I: Means, standard deviations, and two-way ANOVAs

Variable	Emotion present		Emotion absent		Cronbach's α	ANOVA			
	M	SD	M	SD		Effect	$F(1,48)$	p	η_p^2
Agreed items						E	0.85	.36	.017
Competence high	3.6	1.0	4.2	0.9		C	2.35	.13	.047
Competence low	3.5	1.0	3.5	0.8		E × C	1.51	.23	.030
Turns						E	4.14	*.05	.079
Competence high	22.9	9.2	16.9	8.1		C	0.81	.37	.017
Competence low	19.7	9.3	15.8	8.5		E × C	0.18	.67	.004
Rejection rate						E	2.29	.14	.045
Competence high	0.28	0.15	0.17	0.12		C	1.35	.25	.027
Competence low	0.19	0.12	0.18	0.15		E × C	1.66	.20	.033
Dominance					.81	E	0.07	.80	.001
Competence high	5.3	0.7	5.6	1.0		C	1.19	.28	.024
Competence low	5.4	1.3	4.9	0.9		E × C	2.41	.13	.048
Prestige					.83	E	0.19	.66	.004
Competence high	3.8	1.0	4.2	1.2		C	0.11	.74	.002
Competence low	4.2	1.2	4.1	0.9		E × C	0.82	.37	.017
Cooperativeness					.90	E	0.07	.79	.001
Competence high	3.2	0.9	3.0	1.6		C	1.01	.32	.021
Competence low	3.5	1.6	3.4	1.2		E × C	0.00	.98	.000
Trustworthiness					.63	E	0.39	.54	.008
Competence high	4.1	1.0	4.0	1.1		C	0.46	.50	.010
Competence low	4.3	0.8	4.1	1.0		E × C	0.08	.78	.002
Presence					.38	E	0.40	.53	.008
Competence high	4.5	0.8	4.6	1.0		C	0.23	.63	.005
Competence low	4.5	1.1	4.8	0.9		E × C	0.17	.69	.003
Usability					.90	E	0.60	.44	.012
Competence high	5.0	1.7	4.8	1.9		C	0.31	.58	.006
Competence low	4.8	1.6	5.6	1.2		E × C	1.16	.29	.024
Workload					.80	E	2.49	.12	.049
Competence high	5.4	1.4	6.0	0.8		C	2.49	.12	.049
Competence low	6.0	0.9	6.3	0.7		E × C	0.14	.71	.003
Reliability					.81	E	0.16	.69	.003
Competence high	4.3	1.2	4.2	1.5		C	0.05	.83	.001
Competence low	4.0	1.2	4.3	0.8		E × C	0.41	.53	.008

Note. $N = 52$. ANOVA=Analysis of variance; E=emotion; C=Competence.
$^*p < .05$.

TABLE II: Stepwise multiple regression results

Variable	B	SE	β	t	p
Number of agreed items					
Constant	3.33	.46		7.20	<.001
Cooperativeness	-0.35	.09	-.51	-4.14	<.001
Prestige	0.37	.11	.42	3.46	.001
Number of turns					
Constant	-6.05	7.78		-1.05	.30
Dominance	4.71	1.08	.53	4.38	<.001

in this task [17]. In our case, thus, emotion expressions may have added more information for the user to process, leading to an increase in the duration of the interaction, but without contributing to the quality of the final solution.

Another factor for this effect may have been the difficulty of expressing emotion in an industrial robot with limited expression capability. Prior work with the desert survival task suggests that nonverbal behavior can persuade users to follow robot or virtual agents' suggestions [4], [16], [39], [42]. However, these studies did not consider a manipulator robot and did not focus on the expression of emotion. In particular, whereas prior work and our validation study, indicate that people are able to perceive emotion in color, the context for the expression of the emotion may be harder to decipher as noted in the previous paragraph. Prior research suggests that participants are able to make appropriate inferences from others' emotions, but only when the context is clear [35]. Future work, therefore, should explore novel complementary forms for the expression of emotion in industrial robots (e.g., motion), as well as better ways of clarifying the context for the expression (e.g., text or voice explanations).

The fact that emotion expressions slowed down reaching agreement in the early stages of the interaction suggests difficulty in understanding emotions in the early stages of the interaction. Then, the fact that the final item selection was not affected by presence or absence of emotion expression suggests that participants may have started to ignore emotion expressions in the later stage of the interaction. The difficulty of emotion understanding could be explained by polysemy in an emotion expression. Exploratory analysis showed that perceived dominance predicted the length of the discussion. Dominance emotions, including anger and contempt, are antagonistic emotions that accompany an individual's desire to (re)establish autonomy or superiority [19], [22] and damages relationships because they are perceived as a signal of social rejection [12]. In addition, in negotiation studies, anger is known to elicit concessions from the counterpart but it is limited to when the expressor has power [20], [25] (for a review see [21]). If the expressor does not have power, anger causes reciprocal anger in the observer, which is counterproductive to induce concessions. In our study, the robot's anger was simply used to provide feedback that the participant's deselection was a bad decision, but could have been perceived as a signal of social rejection and power. As a result, participants might have not been able to successfully decode the robot's intentions, and subsequently ignored the emotional expression, which may have led to convergence to the same final agreement as in the neutral condition. Since we did not assess participants' ability to decode the robot's feedback, this is speculative and requires further study.

Competence did not affect the final item selection or the length of the interaction, whereas it only contributed to a faster increase in the number of agreed items in the early stage of the interaction. Manipulation checks also indicated that competence was not perceived by the participants. In our study, robot's competence was manipulated by whether to recommend higher or lower ranked items in the list given by a survival expert. However, because the participants did not know the correct answer, they could not justify the recommended item and may not have perceived the robot's competency. If participants are informed in advance by other instructions that the robot is competent, such as that it is an expert in desert survival, this may lead to rapid agreement with the robot's recommendation. Competence (prestige) is known as a quality of leaders as well as dominance [58], and they are factors that change people's decision-making and makes them follow them. Therefore, if robots are able to be perceived as highly competent, the synergistic effect with dominance caused by anger may contribute to rapid agreement, but this is a topic for future research.

Typically, in a desert survival task, the parties are first asked to select five items to measure how they initially rate the items, but we did not measure the initial choice and this is a limitation in the current study. How much the initial preferences matches the robot's preferences is likely to affect the number of turns and the final agreement. In future work, the initial preferences of the participants should be considered.

The interpersonal functions of emotions have been studied intensively in economically distributive or dilemma situations, in particular negotiation [21], [22]. However, there is a fundamental difference between the negotiation task and the desert survival task used in our study. Negotiations usually aim for an integrated solution by estimating the counterpart's limit and preferences for issues that have different monetary value for the two parties [9]. The desert survival task is the same as negotiation in that there are multiple issues and the values of the issues are different between parties, but it is different in that there is a shared goal of eventual survival, i.e., it is a fully cooperative task. Furthermore, considering the original human-robot relationship, the robot is assumed to play the role of a helper. Further research, therefore, is needed to study the effects of anger, joy, and other emotions by robots - especially with limited expression capability - in such collaborative settings.

SUPPLEMENTARY INFORMATION

Supplementary methods: https://osf.io/wth8b

Supplementary movie:

Movie 1: Anger emotion expression https://osf.io/3tj8s

Movie 2: Joy emotion expression https://osf.io/qymrw

Movie 3: Emotion present x Competence high https://osf.io/prsuh

Movie 4: Emotion present x Competence low https://osf.io/rc6jd

Movie 5: Emotion absent x Competence high https://osf.io/9fybs

Movie 6: Emotion absent x Competence low https://osf.io/29nsk

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