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Looking Beyond Collaboration: Socioemotional Positive, Negative and Task-Oriented Behaviors in Human–Robot Group Interactions

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Abstract
In this paper, we aim to increase the understanding of human–robot interaction by considering the goal orientation displayed by the robot (i.e., competitive vs. cooperative) and the role displayed by each player (partner vs. opponent) in an entertainment group scenario. Sixty participants engaged in a card game called Sueca (two robots and two humans). Each participant played with each of the other players, and the goal orientation was manipulated by the set of verbal utterances displayed by the robot. Using a coding scheme based on Bales Interaction Process Analysis, the video-recorded interactions were analysed in terms of socioemotional positive, negative and task oriented behaviours. A marginal multilevel modelling analysis yielded significant interactions between the robotic addressee and the role the robot displayed in the socioemotional and task-oriented behaviours. Overall, our main results demonstrated the following: (1) Participants directed more behaviours towards partners than opponents, although most of these behaviours occurred between humans when they were partners. (2) When comparing players in the role of opponents, participants directed more socioemotional behaviours towards robots than towards the other human player. (3) No difference in task-oriented behaviours was observed among any of the players in this condition. These results suggest the occurrence of different behavioural patterns in competitive and collaborative interactions with robots that might be useful to inform the future development of more socially effective robots.

Keywords Human and robot interaction · Groups · Collaboration · Competition · Games · Autonomous robots

1 Introduction

Socially embodied robots are interactive agents to which "…social interaction plays a key role" [22] (p. 1, emphasis added). Thus, this type of robot should be able to interact with and adapt to humans and other robots across a broad range of dynamic interaction settings [13]. Given that the goal of designing social robots is to build relationships with people, social robots need to function in a fundamentally different way than other types of robots, such as industrial robots [55]. To establish meaningful social interactions with humans, social robots must be able to display an array of human characteristics, of which emotions can be an essential element [44].

Previous research using social robots has demonstrated their potential across a large range of areas (spanning from educational [45] to care-taking uses and [26]) and across different social environments (varying, for example, in number

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of intervenients or levels of structure). These approaches, which increasingly attempt to accommodate the complexity of everyday social interactions, allow for the assessment of group specific relational dynamics in human and robot interaction (hereinafter, HRI). From a multiple-user collaborative standpoint, robots have been found to elicit a broad range of social responses and to be effective teammates, therefore emphasizing the potential value of these robotic agents to integrate human groups, teams and social contexts [26]. As such, in this work, and consistent with the need to analyse HRI in complex environmental and social settings outlined by other authors [13,14]our goal is to analyse different dimensions of social HRI in small mixed groups in an entertainment context.

This work also stems from the authors' interest in this topic, and it presents an extension to the work presented in [47]. However, the present paper significantly expands the work proposed on the latter, by including the analysis of a larger number of behaviours and dimensions. This study is also based on the same sample of study 2 reported in the paper [18]. Nonetheless, this paper presents a novel perspective compared to that of the previous study by focusing on observational measures of behaviours (rather than self-reported measures).

To frame our work, we first provide a general overview of the specificities of robots as social actors and how these agents might affect the relational dynamics of the groups in which they are integrated, with an emphasis on entertainment and gaming scenarios. Second, we focus on the social processes in group dynamics, and in particular, the importance of goal orientation (i.e., competition and collaboration) and the roles played by social intervenients (partners and opponents). We also report the results of a user study involving a card game entertainment scenario called Sueca. In particular, we describe the effect of the addressee (human, collaborative robot and competitive robot) and the role displayed by each player in socioemotional (positive and negative) and task-oriented behaviours. Finally, we discuss the implications of these results to the development of social robots and outline possible avenues of research that might contribute to a better understanding of social group HRI.

1.1 Looking Beyond Collaboration Relationships in HRI

As "robots leave the factory floor and enter human environments", it becomes increasingly more relevant to consider how different types of interaction impact the relationship between human and robotic agents, and how these interaction differ according to the specificities of the type of social relational dynamics among agents ([30], p. 1, emphasis added). Thus, we need to look beyond what happens when people use the aid of a robot, or a teleoperated agent, to achieve a goal, and focus our attention on what happens when people collaborate with a robotic autonomous agent in a task [30]. Collaborating or establishing a partnership relation with another individual or a robot requires the person, to some level, to relinquish control and act jointly with his/her partner (rather than "acting upon" the other; [27]). The concept of collaboration (often used interchangeably with the concept of cooperation) is complex, involving a joint action or effort with one or more external parties towards a common goal (for a discussion, see [35]). This type of relationship has been analyzed in social sciences, both inductively and deductively (e.g. [25,30] respectively) and its specific relational dynamics is recognized by many authors (e.g. [5]). In HRI, research suggests that social robots can be effective partners, and collaboration with these social agents seems to have the potential to yield positive outcomes for the user [31]. For example, in task-related interactions, social robots have been used to aid in surgical procedures (many times in group contexts) [56], in industrial or organizational settings [40] and in educational contexts [24], often improving the practical and task-related outcomes of users.

Robots have also been used to improve group social processes. For example, in [32], the authors successfully used a robot to moderate the conflict in a team-based task, thus, suggesting that robots can have a role in affecting core team processes. The authors have found lower levels of perceived conflict in the condition where the robot uttered repair statements (after a confederate in the experiment created a conflict situation by personally attacking one participant), compared to the condition in which the robot uttered a non-related statement, and the condition in which the robot did not intervene. However, collaboration is only one of the ways that humans and robots are likely to interact in the future.

Despite its ubiquity, competition is a form of interaction far less explored than its counterpart in HRI. In HHI (Human–Human Interaction), some studies have hypothesized the existence of a *friend or foe* mechanism based on the evaluation of the other social agent intentions [15]. This hypothesis is based on findings from game-theory studies that suggest the existence of a reciprocity principle that is applied in social exchanges. As this classification (i.e. friend-or-foe) is postulated to be an input in the decision-making process, the identification of another social agent's intentions can, thus, affect one's behavioral responses towards it. The identification of intentions, however, is not straightforward since intentions are internal states of an individual and as such, not easily discernible. In this sense, the recognition of intentions can be affected by many external and contextual cues that affect the framing of the other individual' intentions and roles in a specific strategic situation. Context matters because it provides the individual with cues about the others intention, that are then incorporated into a mental model that informs the individual about the course of action to take. This type of role manipulation was demonstrated to have an effect in the degree of trust (i.e. partners tend to be judged as being more trustworthy than opponents [15]. Furthermore, it was also demonstrated to have an effect on the engagement in prosocial and pro-self behaviors [19].

1.2 Entertainment and Gaming Scenarios with Robots

It is argued that people like to play games because they provide an opportunity to alter or organize their internal experiences [39]. The large amount of different games, in different formats, in distinct cultures all around the world, bears witness to their pervasiveness and universality. Some games have an educational purpose (i.e. serious games, for a review see [60]), whilst others focus mainly on the entertainment aspect [39]. Serious games integrate a learning or educational component, either by changing the learners' motivation or by altering the cognitive processes associated with this activity [60]. In this context, robots have been used with a large variety of social groups in educational contexts, through the use of games. In particular, robots have been integrated in entertaining scenarios both with human agents [36] and with other robots (e.g., [34]). Robots and synthetic agents have also begun being designed to play several fun games that involve interaction with humans, such as rock–paper–scissors [1], I spy [59] or dominoes [11]. Some of these games require physical interaction with the other players (such as soccer), whereas others can be played by means of solely verbal interactions (such as I spy), although involving some sort of external physical awareness by the robot (in this case, vision). Furthermore, games involving some degree of strategic abstraction include Risk [50] and chess [38]. In gaming scenarios, robots can be used with a varying degree of real physical world actuation, i.e. they can play together with humans in a virtual manner or by means of other technologies such as augmented reality or digitally supported interfaces; or become physical actors, occupying the roles and functions that a human player, in a similar context, would occupy [6]. To be effective team mates or opponents, robots must display a wide range of affective-related characteristics, such as being able to recognize the affective state of the human players, model the state of its human partner and express emotional and affective behaviors congruent with each game situation [6]. Current attempts to embed robots with the ability to recognize humans' affective states has taken a multi-modal approach by including for example, the recognition of facial emotions through specialized software and physiological data (e.g., [61]). However, this possibility has not yet reached an optimal degree of accuracy [6]. Game playing scenarios, not only offer an interesting situation to analyze different relational dynamics, but present advantages compared to other less structured scenarios. According to [6] this is because game scenarios usually involve well-known rules and structured interactions that result from those rules. This, in turn, allows the robot to predict, with a fair degree of accuracy, what the users' affective state will be in each game situation (for example, losing), and thus, engage in interactions that have in consideration the human players' affects, which ultimately will allow the robot to respond and affect human emotional states. Moreover, other behaviors, such as gaze, can also be easy to model in these types of scenarios because players follow a predefined set of turns while playing (more specifically in trick-taking games) and can thus be previously defined [6].

1.2.1 Collaborative and Competitive Gaming

Collaborative and competitive gaming strategies vary in the extent that they involve different goal orientation [53]. In gaming, collaboration and competition present different characteristics capable of evoking different behaviors from players. For example, Sheese and Graziano [53] suggested that competitive gaming increases aggression when compared to collaborative gaming, which is consistent with previous research linking competition to aggressive behaviors [12], and one explanation may be related to the increase of negative emotions such as anger or frustration related to their opponents' behavior of blocking or hindering the individual from achieving his desired goal [2]. Other emotions, such as anger or hostility, and negative socioemotional expressions such as arguments or disputes are likely to occur in this context [12] due to increased levels of negative tension between opponents. Thus, negative feelings and behaviors may trigger interpersonal conflict. In contrast, in collaborative situations the behavioral tendency is affiliative and of social support. Even in competitive games, the display of collaborative orientation (e.g. by promoting feelings of comradery) can be sufficient to prime feelings of cohesion which, in turn, may reduce hostility and interpersonal conflict [2]. Furthermore, in games played in a group setting, both actual and perceived levels of competition tend to increase (e.g., [8]). Group size seems to affect this dynamic, by creating a more overt type of competition and providing more individual autonomy to each person that openly attempts to achieve his/her own goals [42]. On the other hand, in collaborative oriented game scenarios, group size is positively correlated with goal attainment and, consequently, negatively correlated with perceived competitiveness and individual achievement [20]. However, much of the research conducted so far in collaborative and competitive gaming has focused mostly on video games. Video gaming differs from other games, because it is usually conducted online or in virtual environments, rather than face-to-face.

In HRI, some authors have begun to delve into how humans interact with robots in competitive gaming scenarios [48,57]. A shortened analysis of the data presented in this paper has suggested the existence of different interaction patterns in group interactions with robots displaying different roles and goal-orientations (namely, gaze behavior) [47]. Another study exploring the role of goal-orientation in a one-on-one gaming interaction scenario has suggested that humans can feel more positive and engaged in the task when interacting with a robot in a competitive rather than a collaborative situation [46]. The goal of the present study is to analyze socioemotional and task-oriented behaviors within HRI in the context of an entertainment scenario using the Bales Interaction Process Analysis [7], and taking into account the goal-orientation (collaborative, competitive) and the role (partner, opponent) displayed by each agent.

2 Goal and Hypotheses

In this work, we were interested in analyzing how humans and robots interact in small mixed groups and how their interaction dynamics changed according to the roles they played (partner or opponent) and to whom the behavior was addressed (i.e. the addressee: human, competitive robot, or collaborative robot). Specifically, we measured socioemotional behavior (positive and negative) and engagement in task-related interactions towards another human and two robots displaying different goal orientations (collaborative and competitive). In this context, we expected to observe the following:

– *Socioemotional Behaviors*
  A higher number of socioemotional interactions directed at the human player compared to the robots, and more frequently displayed towards partners compared to opponents. These results will resemble an ingroup/outgroup bias effect that often occurs in HHI. In general, positive socioemotional interactions tend to be more directed at members of the perceived ingroup (partners and humans) compared to members of outgroups (opponents and robots). In addition, based on reciprocity hypotheses, we expected to observe higher socioemotional positive interactions towards the collaborative robot in comparison to the competitive robot. Also, we expected that a high number of negative interactions towards the competitive robot would occur compared to the collaborative robot.

Information sharing is part of group processes involving task-related interactions. However, the equilibrium (or ratio) between these task-focused interactions and the more relational (or socioemotional) interactions seems to vary. Task-oriented interactions seem to be the most common, followed by socioemotional positive and then socioemotional negative interactions. Past studies focused mostly on formal tasks (such as problem solving in the context of jury trials [16]), rather than on entertainment. Given that the latter seem to be more relational-oriented (rather than goal or task-oriented), we expect to observe:

– *Task-Oriented Behaviors*
  A higher number of task-oriented interactions towards the human player than towards both robots, regardless of their roles (partner or opponent).

3 Method

3.1 Participants

This study included 60 participants, grouped in pairs (38 male and 22 female), between 17 and 40 years of age ($M = 23.85 \pm 3.92$). One additional pair of participants took part of the study, however, their data was not analyzed because we were unable to record the data from their partners.

3.2 Task

Participants were requested to play Sueca card game with three other players: another human participant and two robots. This game requires four players so that each pair of players is grouped as partners and competes against the two opponents assigned to the other team. In our experiment, participants took turns playing as partners to each of the other three players (the other human participant and two robots) and played a round of three games with each. A detailed description of this game is available in [3] and brief description of its rules can be found bellow.

Sueca is a Portuguese card-game played by two teams of two players and the goal of each team is to score higher than the other team. This game is played with forty cards of a traditional French deck, which can be achieved by removing the ranks from *8* to *10* and each player starts with a hand of ten cards that are randomly distributed. The total of 120 points is equally distributed per suit according to the ranks: {*A*, 11 points}, {*7*, 10 points}, {*K*, 4 points}, {*J*, 3 points}, {*Q*, 2 points}, and {*2–6*, 0 points}. It is considered a hidden-information game as each player can only see his cards. Similarly to other trick-taking card games, a trump suit is randomly assigned at the beginning of a game and any rank of that trump suit beats the other suits. In each of the ten tricks of a Sueca game, players sequentially play one card starting with the player that won the previous trick. The first card of a trick defines the leading suit that other players need to follow during that trick. Unless they are out of the leading suit, they are not allowed to play another suit even the trump. If a player breaks this rule and later in the game reveals he actually had the suit he missed before, also known as “renouncing”, the game is immediately over and his team loses. The winner of a trick is the player that played the most valuable card (in terms of points) of the trump suit or of the leading suit, depending if there were or there were not trumps played, respectively. The winner of the trick sums the points of the four cards to his team’s score. In the end of the ten tricks, the points of the winning team are converted to victory points according to the following rules: [60–89] points convert to 1 victory point; [90–119] points convert to 2 victory points; 120 points or the opponents have “renounced” convert to 4 victory points. Usually, Sueca is played repetitively in a round N games by the same teams and victory points dictate the winning team in that round.

The playing dynamics and the most common strategy adopted by human players consists of leading with the highest scored cards at the beginning of the game, when the probability that the other players have cards to follow that suit is higher. Nevertheless, experienced players also try to communicate non-verbally with their partners when they are out of a certain suit so that they can use the trump suit and win the trick. Overall, both players in the same team contribute to the goal of winning the game either by offering high scored cards to a trick they can win or by preventing the other team from winning a trick. As such, the final score is attributed to the team, instead of the individual players.

In our experiment, the two robotic players assumed distinct traits, one was more competitive while the other was more collaborative. The artificial intelligence techniques used for the decision-making of their playing capabilities as well as the validation of their characters are available in [18].

3.3 Materials

Two Emys heads[1] were programmed to interact autonomously with the two human players during the game. These two robots displayed gaze behavior, emotional facial expressions, and speech, triggered according to a set of predefined game events. The programming of the robot’s behaviors was based on the way humans play. A full list of the utterances can be consulted and is available in [4]. Overall, both robots had a total repertoire of 840 utterances, which were triggered by game related events and were accompanied by congruent gaze and facial emotional expressions. For example, if the robots’ team lost a trick, the robot would display sadness, whereas if their team won, the robotS would display joy. A character validation study described in [18] showed that of both robots the competitive robot was rated as being more competitive than the collaborative robot, whereas the collaborative robot was described as being more helpful, more relational oriented and providing more emotional security than the competitive robot [18]. Additionally, the collaborative robot was evaluated higher on the Relationship Assessment Scale [29] than the competitive robot and higher on likeability (using the Godspeed Questionnaire, [9]). Moreover, both robots displayed similar eye gaze behavior and gameplay competences (as described in [18]), which was achieved by implementing the same algorithm to determine game moves in both robots. In addition, both robots were perceived as equally competent [18]. Finally, participants used a multi-touch game table and played the Sueca game using a traditional French deck of cards with fiducial markers printed in the back, thus contributing to a naturalistic setting for the interaction. To record the interactions, two video-cameras were used and placed facing each of the human participants.

3.4 Procedure

A convenience sample of participants was recruited on the campus of a major technology institute in Portugal. Although participation was voluntary, participants were offered a voucher for a movie ticket with the monetary value of 6 euros and 20 cents. The anonymity and confidentiality of the data collected was assured at the beginning of the experiment. After participants signed the informed consent, which included a request to record their interaction with video and sound, how to use the multi-touch screen table was explained to the participants.

After that, participants were requested to start playing a set of three Sueca games with the other human player (one gaming session). Upon ending the first session, participants played two sessions, one with each robot (competitive or cooperative).

3.5 Coding Scheme: The Interaction Process Analysis

To assess relational dynamics in this scenario, a coding scheme based on Bales’ Interaction Process Analysis (IPA) for small group interactions [7], was developed. We decided to use IPA due to its wide acceptance as a tool to identify group problem solving and decision-making processes, and because of its long history and broad application in communication studies. Table 1 presents the categories and behaviors included in the coding scheme. One independent coder has analyzed the totality of the video-recorded interactions. Following the guidelines proposed by [17], two other coders were requested to code one third of the observations. The observations were selected randomly and all the coders were blind to this study goals and hypotheses. Furthermore, the behavioral coding was made using specialized software

[1] Developed by FlashRobotics: For more information, see: https://emys.co.

(Observer XT, v. 11.5).[2] The final coding scheme included 47 behaviors organized in several dimensions (see Table 1). The verbal and non-verbal behaviors were grouped in three categories as suggested by Bales' IPA [7]: (a) Socioemotional Positive Behaviors, (b) Task-Oriented Behaviors, and (c) Socioemotional Negative Behaviors. In the first category, we included behaviors related to displays of solidarity (e.g., "It's ok, I also renounced in the last game."), providing help (e.g., helping the other player distributing the cards) and raising the other players' status or rewarding him/her (e.g. complimenting him/her or a move he/she did, see image a in Fig. 1).

In addition, we coded behaviors related to tension release, which included making jokes and displaying satisfaction, and showing agreeableness (i.e. agreeing with a suggestion or statement made by another player, complying or showing passive acceptance). The socioemotional negative category included behaviors such as showing passive rejection (e.g. ignoring a request from another player), behaviors of formality (e.g. treating the other player with formality), withholding help, asking for help and withdrawing behavior (e.g., stop talking or interacting. Moreover, we have included behaviors of deflating the other status (e.g., saying negative things about another player, "That robot is really bad at playing Sueca!", defending oneself (e.g., "I am usually a good player, but the cards didn't help this time…" and self-assertion ("What? This has to be wrong [the final score]. I played much better than you"). Finally, in the task-oriented dimension we included behaviors related to giving or asking suggestions (e.g., "What do you think I should do now? If I use the trump here, I won't be able to cut his [referring to the opponent] future moves"), asking for or giving an opinion (e.g., "I think your partner [robot] got mad at you for that move.") and asking or giving orientations (e.g., "It's your turn to shuffle the cards").

3.5.1 Operationalization of Behaviors

Each interaction was coded with respect to:

- (1) time and duration;
- (2) addressee [(2a) human player, (2b) collaborative Robot and (2c) competitive robot];
- (3) role held by the addressee [(3a) partner and (3b) opponent];
- (4) type of statement [i.e. (4a) Verbal (including, asking a question or making a statement) and (4b) non-verbal interaction].

[2] Software developed by Noldus. For more information, see: https://www.noldus.com/human-behavior-research/products/the-observer-xt.

Table 1 Coding scheme used based on Bales' IPA: dimensions and sub-dimensions of behaviors, problems and examples of behaviors included

Dimension	Sub-dimension	Problems	Behaviors included
Socioemotional positive behaviors (SPB)	Displays support	Problem of integration	Shows solidarity; provides help; rewards the other player
	Engages in tension release behaviors	Problem of tension-management	Makes joke; displays satisfaction; laughs
	Agreeableness	Problem of decision	Shows passive acceptance; understands; complies
Socioemotional negative behaviors (SNB)	Disagrees	Problem of integration	Shows passive rejection; formality
	Shows tension	Problem of tension-management	Asks for help; withdraws behavior
	Shows antagonism	Problem of decision	Deflates others' status; defends himself; asserts himself
Task-oriented behaviors (TOB)	Gives/asks suggestion	Problem of control	Gives suggestion; asks for suggestion
	Gives/asks for opinion	Problem of evaluation	Gives opinion; asks for opinion
	Gives/asks orientation	Problem of orientation	Gives orientation; asks for orientation

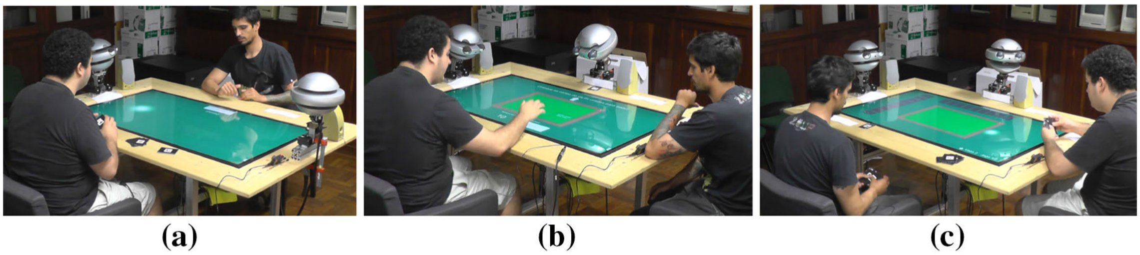

Fig. 1 **a** Participants play in partnership with another player; **b** participants play with each of the robots; **c** participants swap places and play with the other robot. Participants play with a deck of French cards, whereas the robots play with virtual cards and are attached to a multi-touch table and equipped with sound columns, during the course of the game

In addition to IPA [7], we coded gaze behavior but these results will not be analyzed here as they already were reported elsewhere [47]. Overall, each participant played three sets of three individual games (hereinafter, each set of three games will be referred as one session) with each partner. Each session was coded separately for each of the human players involved and overall 6505 behaviors were coded (see Table 1). Agreement among the coders was excellent, with values ranging from 82.82 to 98.07% (M = 92.51%); Kappa = .92.

4 Results

4.1 Descriptive Analysis of the Frequency and Directionality of Behaviors

Of the total number of observed behaviors, nearly 87% were directed at the other human player. The remaining were distributed between the competitive robot (7.2%) and the cooperative robot (5.4%).

Considering the total of behaviors directed at the human player in all dimensions (i.e. n = 5688), 50% were task-oriented, and 41% were socioemotional positive behaviors. The remaining 9% were socioemotional negative behaviors. Considering the behaviors towards the competitive robot (i.e. 465), nearly 81% were socioemotional positive behaviors, followed by socioemotional negative (14.2%) and task-oriented (5%). Finally, regarding the behaviors directed at the collaborative robot (n = 352), nearly 80% were socioemotional positive interactions, 15% were socioemotional negative and 5% were task-oriented behaviors.

4.2 Hypotheses Testing

Marginal MultiLevel Modelling (MMLM) was conducted to account for the interdependence between the dyads of human players. We used restricted maximum likelihood estimation (REML), and three models were estimated: one for the rate of each major dependent variable, i.e., socioemotional positive, negative, and task-oriented behaviors. The rate of behaviors was calculated by dividing the total number of occurrences of the behaviors in each dimension by the total duration of the game session (measured in minutes). The two humans in the group were considered indistinguishable as they were not differentiated by any characteristic that could affect the outcome. Because each participant was nested within his own group, we treated the dyad as the unit (the average score for the dyad) and nine repeated measures were computed considering the addressee and the role displayed. The within-dyad standardization was also conducted to adjust for the spread of the distribution, i.e., subtract each dyadic raw rate of behaviors from the overall mean across the nine types of interactions divided by the standard deviation (Z = (Observed Rate − M)/SD). These Z-scores values allowed to estimate how many standard deviations each behavioral dimension were above or below average, regardless of the size of that deviation, and adjusted for the dyadic differences in response variance. Thus, our data was centred around a mean of zero and the standard deviation is 1. Z-scores around zero indicate that the behavior was identical to the mean, whereas positive or negative scores indicate the behaviors were above the mean or below the mean, respectively. For each model we considered a factorial design with a 3 (addressee: Human, Competitive Robot, Collaborative Robot) × 2 (role displayed during the game: partner or opponent) fixed effects. The MMLM treated all nine combination of the human–robot interactions as repeated measures and a diagonal covariance structure was applied. We also investigated compound symmetry and unstructured variances for the repeated measures, but these models did not converge for the three dependent dimensions. Also, the model for the diagonal structure had a better fit than an auto-regressive structure in all the three models with the predictors. Instead, using the diagonal structure, the variances for the repeated measures were considerably different for each of the nine possible combinations, thus providing evidence that this structure is the most appropriate to examine our models. In addition, we estimated the models fit by comparing each of the three models with the predictors (addressee, role, and the interaction between the addressee and the role), with the correspondent models with no-predictors. For these models' fit comparisons, we used the full maximum likelihood (ML) instead of REML for being considered more valid to estimate the fixed effects change. However, to make the inferences with the predictors the REML was used as recommend by [28]. The Likelihood ratio Chi-square test (LRT) was used to estimate the differences in deviances between the no-predictor models and our proposed models with the three predictors. Thus, in the no-predictor models we have 10 parameters (one for the intercept and 9 for the repeated measure), and in the proposed models 15 parameters were used (one for the intercept, 5 for fixed effects, and 9 for the repeated measure). To reduce the chance of type I statistical errors, Bonferroni adjustments were applied. The LRTs for the comparison between the two nested models for each of the three dependent variables were statistically significant: $\chi^2(5) = 351.43$, $p < .001$ for socioemotional positive behaviors, $\chi^2(5) = 218.62$, $p < .001$ for socioemotional negative behaviors and $\chi^2(5) = 215.58$, $p < .001$ for task-related behaviors.

4.3 Socioemotional Positive Behaviors

The MMLM with the 3 (addressee) $\times$ 2 (role) design for socioemotional positive behaviors yielded significant main effects for the addressee and the role but also a significant interaction between the addressee and the role (all $p < .001$, see Table 2), indicating that the effects of the addressee were dependent on the level of the role. Thus, we examined the interaction by running the simple effects of the addressee within each level of the role (opponents and partner). The results suggested that when the other player was a partner, participants expressed more positive behaviors towards the human player than towards either one of the robots (see Fig. 2, $p < .001$), either the collaborative one ($d = 2.47$, 95% confidence interval (CI) [1.99, 2.95]) or the competitive one ($d = 2.38$, 95% CI [1.92, 2.85]). In fact, these positive behaviors towards the other human player were the only ones that were above the mean. Nevertheless, although less frequent, the number of positive behaviors was higher for the collaborative robot compared to the competitive robot ($p < .001$, $d = -1.01$, 95% CI [-1.39, -0.63]).

Interestingly, when the other player was the opponent, participants expressed less positive behaviors towards the human player than towards either the competitive robot ($d = -1.59$, 95% CI [-2.00, -1.19] or the collaborative robot ($d = -1.67$, 95% CI [-2.09, -1.26]), all $p < .001$. No statistically significant difference was observed between the amount of positive behaviors directed at each one of the robots when they were opponents ($d = -0.18$, 95% CI [-0.54, 0.18], $p = .97$).

Table 2 Main and interaction (I) effects, degrees of freedom (df) and descriptive interpretation of the results

	Addressee F(dfn, dfd)	Role F(dfn, dfd)	I F(dfn, dfd)	Interpretation
Socioemotional positive behaviors	349.39 (2, 190)	270.19 (1, 182)	656.44 (2, 190)	Partners: Hum > Collab > Compet; Opponents: Collab ≈ Compet > Hum
Socioemotional negative behaviors	168.50 (2, 145)	262.39 (1, 96)	104.70 (2, 145)	Partners: Hum > Collab > Compet; Opponents: Collab ≈ Compet > Hum
Task-oriented behaviors	959.70 (2, 103)	1775.90 (1, 72)	969.03 (2, 103)	Partners: Hum > Collab ≈ Compet; Opponents: Hum ≈ Collab ≈ Compet

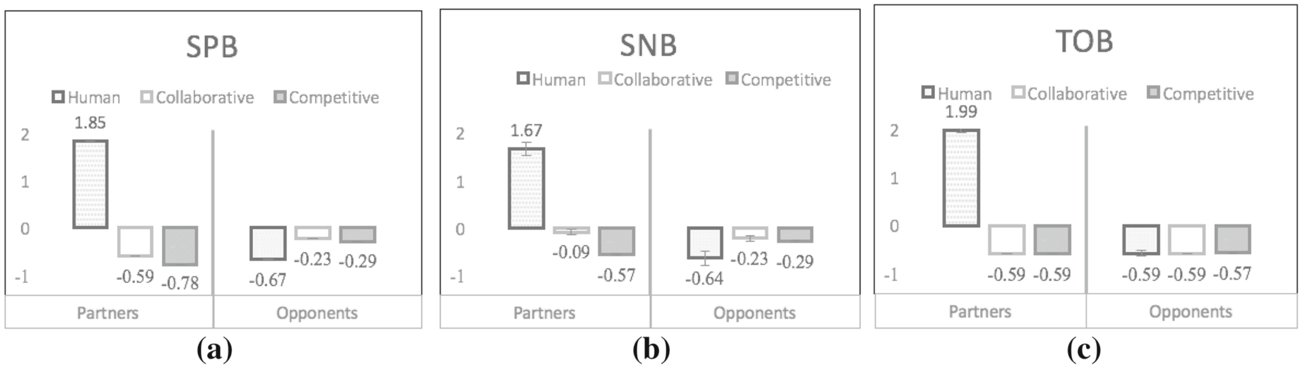

Fig. 2 Mean Z scores of behaviors for the socioemotional positive (SPB), negative (SNB) and task-oriented behaviors (TOB)

4.4 Socioemotional Negative Behaviors

The MMLM for the socioemotional negative behaviors also yielded significant main effects for the addressee, the role, and an interaction between these two variables (all $p < .001$, see Table 2). The interaction suggested that when comparing the different players in the role of partners, participants also directed more negative behaviors towards the human player than towards the collaborative ($d = 2.10$, 95% CI [1.65, 2.54]) and the competitive robots ($d = 2.78$, 95% CI [2.28, 3.28]).

Again the number of behaviours directed at the other human when he/she was a partner were clearly above the mean, in comparison to all the behaviors expressed in the other conditions. Nevertheless, there were also more negative behaviors towards the collaborative robot than towards the competitive one ($d = 1.55$, 95% CI [1.95, 1.14], $p < .001$, see Fig. 2). When comparing players in the role of opponents, participants directed more negative behaviors towards the collaborative robot than towards either the competitive robot ($d = -1.41$, 95% CI [-1.81, -1.01]) or the other human ($p < .001$). In this instance, no difference was observed between the competitive robot and the other human player ($d = -2.75$, 95% CI [-3.26, -2.26], $p = .092$).

4.5 Task-Oriented Behaviors

For task-oriented behaviors, there were also significant main effects of the addressee, the role, and an interaction between the variables (all $p < .001$, see Table 2). In particular, simple effect analyses comparing the different addresses in the roles of partners and opponents, revealed that in the condition in which they were partners, we found again that participants directed more task-oriented behaviors towards the other human player than to either the collaborative ($d = 6.31$, 95% CI [5.44, 7.19]) or the competitive robot ($d = 8.08$, 95% CI [7.01, 9.17]). However, no difference was observed between the task behaviors directed at both robots when they played as partners ($p = 1$). In contrast, when comparing the different players in the role of opponents, we did not observe significant differences among any of the addresses ($F(2, 154) = 1.09$, $p = .34$), meaning that participants interacted equally with all the other players.

5 Discussion

Our goal in this study was to investigate how the role played by each agent (opponent or partner) and the different goal orientations displayed by the robots (collaboration or competition), affected HRI in small mixed groups. We examined behavioral indicators of socioemotional (negative and positive) and task-oriented behaviors, using an entertainment game scenario. The data gathered for our study allowed us to observe that participants interacted more with the human than with the robots (as indicated by the fact that 87% of all behaviors observed were directed at the other human player). In addition, approximately half of all the interactions directed at the human player were task-oriented, followed by positive interactions (41%) and negative interactions. In contrast, the majority of behaviors (80%) directed at the robots were socioemotional positive behaviors. Also, participants interacted more with the other human when he/she played the role of a partner compared to when he/she took was the opponent, suggesting the important effect of the role played by each intervenient in the overall interaction. This fact is also confirmed by our hypotheses test aimed at comparing the differences in behaviors towards each addressee according to the role they played. In all instances in which both humans were partners, the number of coded behaviors were higher than average. A smaller number of behaviors were displayed towards the other human player when he was the the opponent, and towards robots.

These results suggest a certain disengagement towards robots in small mixed groups that involve more than one human and more than one robot. Recent work by Rossil and colleagues has underlined the need and lack of research on the possible disengagement towards robots in everyday task-related situations (e.g. watching television or ironing) and has begun to explore this phenomenon in home-like scenarios with elders [52]. These authors conclude that disengagement (resulting from the feeling of being disturbed by a robot) can be associated with several factors, including the cognitive level of the demand resulting from the task and the pose or distance at which the robot was from the user. However, given that our study involved a a different type of scenario (not only it was a group scenario, but it was also entertainment-based), other factors might have influenced the behaviors towards robots. More research aimed at understanding what are those factors and what are the mechanism through which those factors influence HRI is needed. Our results also suggest that participants direct more socioemotional behaviors (both positive and negative) towards the collaborative robot than towards the competitive robot when each displayed the role of partner. This result is partially inconsistent with our hypothesis predicting that participants would direct more positive behaviors towards the collaborative robot and more negative behaviors towards the competitive robot. One possible explanation for this can be due to the fact that participants might have perceived the competitive robot as a social threat and thus, decided to direct more socially positive behaviours towards it as a way to appease it [37]. This is in line with a prominent psychological theory on the processing of social threats and ingroup-outgroup bias and needs further exploration in the field of HRI (c.f. [41]).

In addition, the results in both socioemotional dimensions (positive and negative), n.b., when looking at the condition in which players display the role of opponents, participants seem to direct more behaviors towards the robots than towards the other human player. In this condition, participants interact equally with both robots, and in very similar amounts in both socioemotional dimensions, and they direct more positive and negative behaviors towards the robots than towards the other human player. This is an interesting finding for researchers and developers alike because it suggests that the role displayed by the robot can be an important factor in balancing the number of interactions directed at each intervenient in mixed social entertainment scenarios. Furthermore, as much of the research in HRI has been aimed directly at exploring the many benefits of collaborative interactions among humans and robots, this finding also suggests that competition can elicit certain interaction gains (in this case, higher engagement with the robots), which is an important consideration from a social design standpoint.

Our results also suggest that participants looked at the robots as interactive competent members of the interaction (rather than animated toys or lifeless machines). In fact, participants directed positive affect towards the robots (e.g., apologizing) and saw them as competent agents in the context of the game (by asking them for suggestions, for example). This result, as well as the reduced frequency of negative interactions, is similar to other findings in HRI, observed by Shin et al. [54] using portions of the same coding scheme used here [7], and lends further credence to the CASA paradigm (Computers Are Social Actors) by re-affirming the social nature of robots in human environments. However, task-oriented behaviors were predominantly directed at the human player when he/she was playing as a partner. This distinction disappeared when we compare the same players displaying the role of opponents, thus suggesting that, in this situation, participants interacted equally with all the players. This result might be because humans are overall more responsive than the robots (and thus, preferred in social contexts) and also because humans prefer to interact with entities more similar to themselves in group situations [58]. In particular, despite our robots being able to autonomously interact with participants, the chain of information was unidirectional, i.e. robots were not capable of understanding what participants were saying and respond accordingly. Moreover, when the other human player was an opponent, participants might not have interacted more with him/her because, given that Sueca is a competitive game, asking directions from their opponent might not be a smart move.

Moreover, in the particular case of task-oriented behaviours, there seems to be a large discrepancy in the distribution of this type of behaviours when comparing the target of said behaviours (human or robot). Indeed, in our study we observed that when the target of the interaction was another human, approximately half of all behaviours were task-oriented, compared to only approximately 5% when the target was a robot. A possible explanation for these results goes once again back to the level of interactivity and socially contingent behaviour of the robots and to the nature of this type of behaviours. Task-oriented behaviours included asking and/or giving suggestions, opinions and orientations. Doing this requires that one has an understanding of the social and task-oriented aspects of a situation (e.g. to provide a suggestion regarding what another person should play next, one must be able to see several moves ahead in order to judge the potential success of each move). It also requires conditional reasoning in the sense that one must consider potential gains and not only immediate gains (e.g. One might suggest that the other player foregoes a smaller immediate gain (here defined by winning a smaller amount of points), in order to save a trump card that might be used in a posterior move to gain a higher reward). In this study, the robots used lacked these two important context-processing features (i.e. evaluation of the immediate and potential success of a move). This is a factor that becomes evident to the human players during the course of the interaction and that, thus, results in a smaller number of attempts from the human participants to elicit this type of behaviours from the robots, as a form of behavioural adaptation to the limitation of the robots. Furthermore, it is also congruent with the distribution of socioemotional positive and negative behaviors, in recreational interactions with virtual agents observed by Peña et al. [49] and with the results presented by Mutlu et al. [46] with a humanoid robot.

Overall, from a design and research perspective, this finding underlines the importance and need, not only to build autonomous robots, but also to develop robots that are context and socially-aware and that are not bound to a predefined set of scripted interactions. As suggested by other authors, this feature can improve the creation of rapport between the robot and its' user and thus lead to a more balanced interaction in group situations involving more than one human and/or more than one robot (c.f. [43]). It can also make the situation more engagement by avoiding mental (such as distractions) and social (e.g. unbalanced contributions from group members) limitations to engagement with technological artifacts (see taxonomy proposed by Pohl and Murray-Smith [51]).

Several limitations must also be taken into account. Firstly, we believe that the embodiment of the robot might have presented a limitation to this study. The fact that the robots are composed only by a head might have hinder the scope of interaction by limiting the interaction to verbal interactions, gaze behavior and emotional expressions. The lack of an upper body structure (arms) in the robots imposed restrictions on physical collaborations, which is relevant given that some tasks in Sueca require, either physical collaboration among players or, at least, physical manipulation of objects. For example, only the human players were expected to shuffle the deck of cards because the robots lack of arms. This may explain the fact the behaviors in the category of providing Help (already described in [47]) were only directed at the other human player. The help provided required some degree of physical collaboration and was non-verbal in nature (e.g., passing the cards or picking up a card that fell to the floor), thus excluding the robots' participation in this task, and increasing the number of interactions between humans. Secondly, Sueca is a traditionally Portuguese typical game, not commonly played in other countries. The uniqueness of this task might be a double-edged sword. On one hand, it allowed us to create an interesting entertainment scenario, by leveraging the use of a culturally known game among Portuguese people. This context might have played a positive role in the perception of the robots. The work of [10], for example, has shown a positive bias towards robots expressing cultural cues congruent with the culture of the individual, highlighting the importance of cultural congruence between a robot and humans in collaborative interactions. However, the uniqueness of this task might make its replication by other authors harder due to its' cultural significance and embeddedness. The use of this task by participants from other countries might not have be accompanied by the a similar embedded significance to participants from other countries. To overcome this limitation, we have made available a full description of the Sueca game and a full translated list of the utterances used to manipulate the robots' goal orientations. In addition, the fact that participants always played first as partners may have also contributed to the establishment of rapport towards the other human and, thus partially explain the more frequent interactions between human players observed in our study. The use of a control group composed only by human players might have also served as an interesting ground for comparisons and should be considered in the development of future work.

Overall, our study looked beyond collaboration in HRI by considering how the roles played by robots and humans (partner vs. opponent), and the goal-orientations displayed by the robots (competitive vs. collaborative) affects the relations among humans and robots in small mixed groups. It also applied the IPA [7] to the study of HRI in small mixed groups, thus providing a better understanding of how these variables (i.e., role and goal orientation) influence socioemotional positive, negative and task-oriented behaviors directed at robots and other humans in an interactive entertainment scenario.

6 Future Work

The use of autonomous robots in small mixed group interactions with humans is relevant because it allows the observation of the impact that robotic agents can have in shaping the overall group dynamic and in affecting the interpersonal dynamics among other members of the group. Research paradigms such as the one we developed is a step-by-step effort to create a better understanding of what are the specificities of group HRI and the main factors affecting these dynamics. Although previous research has discussed to a great extent the factors that affect certain domains of HRI in which there is one human and one robot intervenient, only in recent decades have researchers begun to collectively debate the issue of HRI in groups and to systematically attempt HRI's inner workings. . This growing debate has been linear to the growth of technology developments, and it has accompanied the fast-forward moving pace of increasingly capable and autonomous robots that are becoming increasingly accessible, widespread and useful for people in different contexts [23]. Investigating HRI through the lenses of group interaction adds complexity to these social interactions compared to individual responses to an event [33]. Similar to group HHI, HRI in groups is the contextualized product of the interactions among group members that follows a cyclic quest for equilibrium and balance between socioemotional (positive and negative) and task-oriented behaviors [7]. This cyclic recurrence preconized by Bales [7] implies that groups engage in multiple collective actions that successively disrupt group harmony and then restore it by means of some reparative action. The ability of a robot to engage, as an active participant in this cycle, must be, as a consequence, an important factor to take in consideration in the development of robots that are to be seen as effective group members interacting in a realistic and adjusted manner with other people and, possibly, with other robots. To achieve this end, we suggest two possible avenues for future research.

First, although it is likely that groups of humans and robots will collaborate in the future in a broad array of activities in teams, it is also likely that each team has to compete with other teams, or even with individuals within that team for some resources. Thus, further research should be conducted to yield a better understanding of other related questions, such as the dynamics of competing teams of humans and robots, and the role of task-related attributes (e.g., competence) that might be perceived as being important in competitive situations. One possible line of research will be to investigate other well-recognized psychology models of perception, such as the Stereotype Content Model [21], that considers the importance of task and relational related variables, namely warmth and competence. Models like this, can provide a useful framework through which researchers can look at competitive HRI and analyze both within groups and between groups interactions. Secondly, to the best of our knowledge, little is also known about how the role of individual preferences, that have been shown to affect individual preferences in one-to-one HRI, translates to group interactions. In the context of HHI, individuals' preferences for interaction are often influenced, not only by the perception that the individual has of the target of the interaction, but also that that the individual has of him/herself and of the congruence (or lack thereof) among traits considered relevant. For example, in a competitive card-game scenario like the one discussed here, it would make sense to argue that congruence in task related traits (such as, competence or goal-orientation) could positively affect the interaction. In other words, a player that perceives himself as being a very good player and that displays a very competitive goal-orientation, will probably prefer to play with a robotic partner displaying the same characteristics. However, a player that evaluates him/herself as low on competence, might prefer to play with a robotic partner that displays the opposite traits. Thirdly, going back to the results described in this paper, it seems clear that, in group contexts, as indicated by the frequency of behaviors directed at each of the addressees, humans seem prefer to interact with other humans. This lack of engagement towards robots in small mixed groups of humans and robots, when there is another human present, is an issue that begs further investigation. Answering the above questions might yield a better understanding of HRI in groups and, in turn, to reveal information that aids the development of more socially effective robots by allowing the establishment of an optimized interaction process that takes in consideration the users' preferences. This allows for the development of robots that can behave properly and produce adjusted responses in group situations.

In conclusion, we focused on exploring the effect of goal-orientation (competitive and collaborative) and of the role (partner or opponent) displayed by humans and robots participating in a group entertaining interaction. The results described here hint at the existence of a clear preference of interaction towards humans (in comparison with robots) as indicated by an analysis of the frequency of behaviors. This might be explained by an ingroup bias towards the other human player or by a lack of engagement towards the robots caused either by a negative perception of robots in general or by a negative perception of the robots used in this study. Moreover, these results also suggest the incidence of different behavioral patterns for HRI in collaborative scenarios and in competitive scenarios. This urges the need to further explore these type of relational dynamics (i.e. competition and collaboration) in group scenarios involving more than one human and more than one robot.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

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