Friends or Foes? Socioemotional Support and Gaze Behaviors in Mixed Groups of Humans and Robots

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ABSTRACT

This study investigated non-verbal behavior and socioemotional interactions in small-groups of humans and robots. Sixty-participants were involved in a group setting in which they were required to play a card game with another human and two robots (playing as partners or as opponents). The two robots displayed different goal orientations: a competitive robot (named Emys-) and a relationship-driven cooperative robot (named Glin+). Video recordings of the interactions were analyzed in three game play sessions. Eye gaze and socioemotional support behaviors were coded based on Bales' Interaction Process Analysis. Results indicated that gaze behavior towards partners was more frequently displayed to the relationship-driven robot than to the competitive robot and the human partners. In contrast, gaze towards opponents occurred more often towards the competitive robot than to the relationship-driven robot and the human opponents. Socioemotional support occurred more frequently towards partners than opponents, and was also displayed more often towards humans than towards robots. Moreover, in the sessions where the robots were opponents, participants provided more support to the competitive robot. This investigation in small groups of humans and robots provided evidence of different interaction patterns towards robots displaying distinct orientation goals, which can be useful in guiding the successful design of social robots.

CCS CONCEPTS

• **Human-centered computing → User models**; **User studies**; **Collaborative interaction**; **HCI theory, concepts and models**; **Empirical studies in HCI**; **Activity centered design**; **Scenario-based design**; *Social recommendation*;

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KEYWORDS

Human-Robot Interaction, Group, Socioemotional Support, Gaze, Interaction Analysis, Communication

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1 INTRODUCTION

People regularly engage in complex group interactions as part of their day-to-day life, doing so in different contexts and with different targets. From formal meetings to gatherings, our life is inherently social, and many of the activities we experience are organized around small groups. As robots become increasingly autonomous and entrenched in our world, they must be able to engage in diverse activities with humans (e.g., daily activities, entertainment) and thus, become part of our groups. As a result, it is expected that mixed groups of people and robots will emerge in the near future.

Advances in science and technology have already allowed, to some extent, robots to become part of our life, spanning from several different uses that include their integration in educational settings (for a review, see [48], workplaces [49] or health-care [42]). In this context, we believe we are witnessing a paradigm shift, where autonomous, single robots will be replaced by pervasive robotic systems working in symbiosis and in groups with people in their environments [18]. This draws the attention to the importance of studying how humans and robots behave when interacting in small mixed groups [31, 67].This is also an important aspect to take into account in guiding research in groups of humans and robots as it has the potential to yield significant insights about the design of social robots. More specifically, it could yield useful information concerning the understanding of the emergence of explicit and implicit communication patterns in group situations.

Thus, it is important to identify socioemotional responses and other communicational cues that may occur in group interactions when robots are present. As such, in this paper we investigated how human groups and teams are affected by the presence of social robots in terms of their dynamic social metrics, specifically *socioemotional support* and *gaze behavior*. More specifically, we have explored this by using two autonomous robots that exhibit different relational characteristics, goal orientations and motivations. Socioemotional support can be manifested in many ways and it mainly consists of actions that are aimed towards comforting or uplifting others, especially in situations that are considered to be stressful or in any other way hazardous to one's psychological well-being. Situations that require competitiveness skills are known to cause its participants stress [25]. In the specific context of HRI, factors such as stress and the role displayed by the human participant have also been considered as performance shaping factors [62], but an in depth analysis of how these two factors correlate and can shape performance in group situations that require both competitive and cooperative skills and dynamics is still lacking. Competition and cooperation are two ubiquitous ways of interaction in the social context and remain two possible ways that humans and robots can interact in the future. Although, there is enough evidence to assume these different relational dynamics influence interactions among humans and are somehow dependent of the roles played in such interactions, it remains largely unexplored how this happens in the context of HRI.

Taking a scenario of a card game, where both cooperation and competition goals are required, we will analyze how the role displayed by the human and robot players (i.e., partners or opponents) alongside to their characteristics, relate to the way humans socially interact in this scenario. As such, we will consider the gaze behavior, due to its central role in face-to-face communication [69], and also the positive socioemotional support provided to members of the group, given their importance for the effectiveness of teams and groups [38, 41]. However, given the complexity of the dynamics in small groups, there is still no consensus related to how human relations are created and developed among teams and group members [41]. Nevertheless, several proposals have been developed on how to analyze teams and small groups, with a particular emphasis on the importance of the socioemotional domains of communication among group members. We propose the application of the same type of analysis for human and robot teams, in order to obtain a deeper understanding of the role robots can play there. Moreover, we decided to do so by means of qualitative observation in a game play scenario, because literature indicates that this method allows a more comprehensive ingrained analysis of the behaviors in hand [6]. *This paper contributes to the area of Human-Robot Interaction (HRI) by suggesting a direction for understanding the relational dynamics in mixed groups of humans and robots, focusing on both verbal and non-verbal communication messages of socioemotional support and eye gaze behaviors between team members and opponents.* We believe that social models of group interaction are key in the development of social capabilities in robots, ensuring that robots do not disrupt and can indeed adapt to the existing interaction protocols in the teams they integrate. By analyzing human behavioral responses in mixed groups of humans and robots, we envision to contribute for a better understanding on how different roles played by robots in groups, and how their behaviors can be shaped to lead to stronger social and emotional relations with humans.

2 RELATED WORK

2.1 Human-Robot Interactions in Small Groups

Extensive research has been devoted to studying the interaction between humans and robots. Indeed, the highlight of HRI as a research field has been about developing single robots, and studying how humans react or respond to them. Yet, a new trend of research is emerging dedicated to the study of multiple humans reacting and responding to multiple robots, either in small or larger interaction groups [13, 27, 44].

When we think about groups in HRI, different scenarios of interaction are possible. Specifically, we can have a robot interacting with multiple users, or multiple robots interacting with multiple users. Although some of these interactions have already begun to be explored, extensive research needs to address these social contexts by examining these complex relationships and predict how these interactions will occur in the future. Previous studies in this line of research include assessments on how people in real world settings behave, comparing individual versus groups of robots, e.g., [16, 27], or how multiple robots interact with multiple children in interactive storytelling scenarios, underlying the promising character of this approach, e.g., [44].

In the educational context, and considering a scenario of multiple users [1], the concept of group-level emotional climate to model the emotions within small groups of two students was studied, in order for the robotic tutor to understand and support them when a negative emotional group climate arose. A negative emotional climate was triggered when both students were displaying signals of distress. However, when only one of the students was displaying distress the robot would wait for their climate to balance to provide time for the other student to help, sustaining a mixed-support educational environment. Besides this context, groups of robots have been investigated as coworkers with different degrees of humanlikeness (machine– or human–like) and roles [35].

Studies of groups of people interacting with social robots in unstructured real-world environments have been conducted in settings such as an airport (involving large groups) [65] or under conflict situations [66]. Regarding socioemotional cues in HRI, Jung et al. (2013) investigated the role of social signaling behavior in HRI teams by focusing on backchanneling behavior. They concluded that when robots make use of this type of behavior, the team functioning improved and the robots were perceived as being more engaged to the task. Their results showed that social signaling is crucial in HRI, specially regarding team effectiveness, highlighting their importance for the design of robots that are intended to interact with groups of people in task-oriented situations [37]. Body orientation and gaze behavior of a single robot interacting with groups of humans have also been investigated. Researchers have concluded that the different set of gaze behaviors displayed by the robot affected the participants' perception of the robot's motion and that its motion affected human perception of its gaze. This indicates that mutual dependency in the robot's behavior needs to be taken into account jointly when designing a social robot for group interactions [67].

Another study investigated the effect of behavioral mimicry, physical similarity, and eye gaze on the perceptions of social groupings. It was found that behavioral mimicry had the most dominant influence on social grouping, though this influence was modulated by the robot's appearance [52]. People's perceptions towards robots were also affected by the number and type of robots, e.g., [28]. Moreover, people's perceptions of the robot as part of their own group also have an effect in their willingness to interact with it [43]. This result is congruent with ingroup/outgroup membership effects in group interactions, including studies where participants were primed through verbal instruction of a robot with the same appearance as belonging to either their group or to a different group (ingroup and outgroup manipulation) [43]. Results revealed that the ingroup robot was evaluated more positively and with higher levels of anthropomorphism. Findings also indicated that sharing an ingroup membership with the robot led to greater willingness to interact with robots. Additionally, benchmarks for HR-teams were put together to evaluate robots as successful teammates, where having a humanlike mental model and sense of self seem to play an important role [31].

Although these studies are congruent with the increasingly growing paradigm shift from considering HRI as a two-agent interaction (one human and one robot), to a mixed group situation, the need for socially and interpersonally effective robots underlines the necessity of exploring how this type of interaction occurs across different settings. Furthermore, all these studies demonstrate the need for a principled way of looking at these new types of interactions, grounded in the analysis of human-to-human group interactions.

2.2 Behavioral Analysis in Small Groups

To understand and extract the patterns of interpersonal behaviors in human-to-human group interactions, several coding schemes have been proposed, e.g., [47, 55]. In the context of analyzing small groups, the Interaction Process Analysis (IPA), developed by Bales [7] stands as the most widely used across a broad range of areas, including workplace and organizational context, e.g., [4], family systems, e.g., [56], clinical settings, e.g., [46], and also in computer-mediated communication, e.g., [68] involving recreational settings such as playing online multiplayer video games [57]. Notwithstanding, to the best of our knowledge, this model has still not been applied to the context of HRI with small goal-oriented groups. These type of groups are relevant because they present a myriad of similarities to the functioning of day-to-day groups in a large range of settings. Being that, independently of their primary goal (task or relational oriented), all group members will engage in relational interactions, producing and interpreting socioemotional cues that hinder oracilitate group cohesion [41]. As previously noted, the study of these factors in small goal-oriented groups has received little attention and therefore remains a gap in the literature [41].

The approach proposed by Bales [7] considers small groups as functioning social systems. Such systems present the following four functional problems: adaptation to external conditions; instrumental control for performing goal-oriented tasks; expression of emotions and tensions among members of the group; and preservation of the social integration of members as a supportive collectivity. To capture these complex functioning social systems, Bales [7] proposed the IPA, in which two major areas can be distinguished: one is the *socioemotional area*, focusing on the relational dynamics of the group, and including both positive and negative socioemotional behaviors; while the other is a *task-orientated area* and is neutral in relation to socioemotional communication. These areas include 12 content categories, 6 for socioemotional behaviors (3 positive and 3 negative) and another 6 oriented to the task. Bales argued that these two domain areas can coexist, although it is possible to capture which area is predominant and assess either the socioemotional or the task oriented messages when coding behaviors.

In this paper, we focus only on *support behaviors, which are integrated in the positive socioemotional behavioral domain area of IPA*. Research has shown that support behaviors are very important to maintain relations, and thus of extreme relevance for the effectiveness of teams and groups [38, 41]. Positive socioemotional messages in the context of goal-oriented tasks also play an important role in fostering groups' cohesion, offering both content and information about the relation [10]. For example, [57] demonstrated the importance of positive relational messages in the context of competitive online games, which is in line with Bales' assumptions [7] that positive socioemotional responses outweigh negative responses and can act as reinforcement for individual action and task performance. However, in the context of HRI, little is still known about how these relational messages can influence social dynamics in a competitive setting, and specifically what are the traits and goal orientations displayed by embodied social agents more likely to elicit such social dynamics. Extending previous research, *we will also analyze eye gaze behaviors*. The importance of gaze has been thoroughly documented in the context of designing embodied conversational and social agents [51]. Its ubiquity has been demonstrated even in the earlier studies [22] and still remains a relevant research topic up to this day. Specifically, eye gaze behaviors are considered to be an important factor in face-to-face communication, affecting how the agent is perceived [50] as well as task performance [29], while also being a crucial factor in the determination of social outcomes in HRI [5].

3 STUDY DESIGN AND PROCEDURE

3.1 Goal and Hypothesis

Our main goal is to understand how humans respond to other humans and robots in mixed groups in a scenario that is both cooperative and competitive. We were interested in studying how individuals would respond to robots displaying different social orientations (i.e., competitive vs. relationship-driven) and to humans, by also taking into account the specific roles they played (i.e., partner or opponent).

3.1.1 Hypothesis for Eye Gaze Behavior. We hypothesized that participants would gaze more frequently at the human player, since gaze is usually directed to a target that is more familiar [14], makes more movements, and speaks more frequently [32], which we expected to happen in this game scenario. Regarding the gaze directed towards the robots, we expected gaze to be dependent on their role (opponent vs. partner) and characteristics (competitive vs. relational). In light of the literature suggesting that we tend to look more often to stimulus perceived as a threat (threat-related attention bias e.g., [2, 64]), which in this study would be a threatening opponent, we expected that gaze would happen more frequently in the direction of the opponent whose traits would be more competitive (i.e., towards Emys-).

3.1.2 Hypothesis for Socioemotional Support Behavior. We expected to find more frequent displays of support directed to the human player in comparison with the robots [31]. We also expected that displays of socioemotional support behaviors to be more frequently directed at the addressee holding the role of partner than to the opponents. This hypothesis is based on prior research showing that partners or members of the perceived ingroup tend to be evaluated more positively in comparison to opponents or members of the outgroup [34]. Positive evaluations also tend to be associated with displays of positive socioemotional behaviors, and more specifically to support behaviors, considering that in a group interaction context these behaviors are related with positive antecedents, such as the existence of a social network [11], the observation of a certain degree of social embeddedness [59], as well as a positive social climate [45]. However, previous studies in this area were conducted with human subjects; thus, there is the need to test if the same social responses could be applied in mixed groups of humans and robots.

3.2 Sample

To examine the social dynamics of humans and robots interacting in small groups, an experimental study was conducted, in which participants played a card game and interacted with a partner and two opponents in three sessions. A convenience sample of 60 participants (38 men and 22 women) was recruited from an university context, between the ages of 17 and 40 years (M=23.85; SD=3.92). Two additional participants were involved, but because we were not able to record the behaviors from their partners, the data from these two participants was not analyzed.

3.3 Task, Robot and Environment

To investigate the social and emotional dynamics of HRI in small groups and teams, a scenario was devised that required both competition and cooperation for a successful play. The task involved playing cooperatively and competitively a card game entitled Sueca (for a full description, see [3]). As the game activity is played with real cards in a physical environment, the scenario includes a multi-touch table, a deck of physical cards with printed fiducial markers that were recognized by the touch surface of the table, therefore blending and contributing to the naturalistic feeling of the scenario. The card game is played by four players, grouped in teams of two. These two dyads compete against each other. Consequently, in each session the participant has a team partner and competes against two opponents (see fig. 1). We chose this specific scenario because we considered it to be an ideal setting to investigate the social dynamics in HRI, as it requires simultaneously competitive and cooperative behaviors. This setting allowed us to explore how players interacted with each other depending of their role in the game (i.e., partner or opponent).

Two distinct robotic characters were created to autonomously engage in this scenario with two human players. Each robot had two main goals during the task: (1) to play the card game, and (2) to interact with the other players. A similar level of game play competencies was guaranteed in both robots by implementing the same algorithm for computing game moves, which is detailed in [20]. Moreover, the robots have similar embodiments (EMYS[1]) and they also have similar social behaviors, as their baseline for behavior was designed upon a user-centered study described in [19]. Such baseline defines the gaze flow of each robot, as well as the game stages that trigger their verbal behaviors. Their gazing rules basically cause gaze shifts towards the player performing the current game action, which might be, for example, a player shuffling the deck, a player playing a card, or a player winning the trick. When the game action involves a new card on the table, the robots also glance at the top of the table.

In addition, the verbal and non-verbal behaviors expressed by the robots were used to distinguish the different characteristics and goal orientations of the robotic characters, named Emys- and Glin+:

- Glin+ displayed more relationships-driven behaviors – utterance example: *"I am so proud of being in your team!"*
- Emys- displayed more competitive behaviors – utterance examples: *"Watch and learn how this is played"*; *"We have to win this!"*

Overall, both robots were programmed with a total of 840 utterances (419 for the competitive Emys- and 421 for the cooperative Glin+). These utterances are divided in several categories and were programmed to be displayed as a function of the stage of the game (e.g. card shuffling, distribution of cards, loose, win, tie, revoke, and several other card game related comments). The detailed list of utterances displayed by the robots, including their non-verbal behaviors such as the direction of the gaze, glances, and animation of the expression, is available at [54]. Some of the utterances were also neutral regarding the relationship orientation and served as filler expressions in neutral game occasions (e.g. "It's your turn next").

Previous findings with the same scenario and manipulation of the robots, pretested with different participants (study 1 in [21]), have validated through subjective measures that both robots were perceived similarly regarding their competence, but distinctly in terms of their goal orientations, i.e., Emys- was perceived as more competitive, whereas Glin+ was rated more relationship-driven and able of providing more emotional security to the partner.

3.4 Study Conditions

The user study was divided into three sessions, containing a series of three Sueca games each (see fig.1). After each series of three games participants changed partners. Thus, in a repeated measures design with 3 sessions, participants were exposed to all of the treatments conditions, in which they form a team with a human, with Emys- (the competitive robot) and with Glin+ (the relational robot). In session 1, all participants played a series of three games with a human partner. Then, in sessions 2 and 3, participants were assigned to play either with Emys- or with Glin+ as partner, in a randomized counterbalanced order (see fig. 1) .

[1]http://flashrobotics.com/

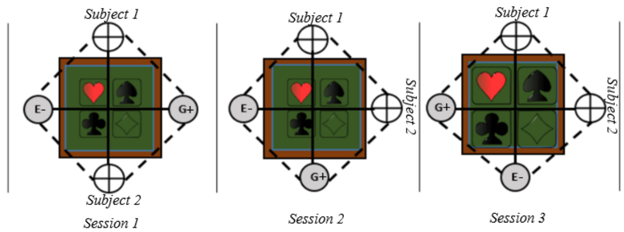


Figure 1: Representation of the three sessions of game play: Full lines indicate partnership relations and dotted lines identify players playing as opponents. Robots are identified by it's initials.

3.5 Measures

We focused on *eye gaze and socioemotional support behaviors*, taking into account the observational guidelines proposed by Bales (1950) IPA [7].

The advantage of using IPA coding methodology is the possibility to isolate and code specific behaviors within each sub-domain, allowing for behavioral fine-grained analysis of interactions among group members (see also [8, 61]). Therefore, instead of coding the socioemotional support behavior sub-domain as a whole, we specifically coded each behavior in this category, such as *solidarity, raising the other status, providing help, and rewarding others* [7].

- **Solidarity** is defined as any action displaying friendliness, affection or companionship towards another player. It was scored taking into account both verbal and non-verbal communication cues. For example, verbal expressions included reassurance statements, such as *"Don't worry, I also did the same mistake"*; expressions of proximity among players, such as calling each other by the first name; interactions aiming to break the ice, such as *"How did you learn about this experiment?"*; use of "we" expressions or any other conveying partnership, such as *"We are a good team"*. Examples of non-verbal expressions included smiling towards another player;
- **Raising the other status** included behaviors such as cheering for the other person, acknowledging his/her point of view, encouraging or praising the other;
- **Providing help** included behaviors such as offering assistance (see fig.2), contributing with one's time or energy into helping another person reaching a goal or completing a task (e.g., *"I know you hate shuffling the cards. Do you want me to do that for you?"*).
- **Reward behaviors**, usually occurring in response to disagreements or displays of antagonism from the other players [7], were coded when acts of pacification occurred, including mediation, conciliation or other behaviors aiming to restore harmony with the other players (e.g., statements such as *"Do not worry, I also did the same during the game without even noticing"*; *"Ok, in the next game we will do as you say"*; *"Let it be, he is just joking. His intention was not to offend you"*).

Figure 2: Example of participants providing help distributing the cards.

4 DATA COLLECTION

The anonymity and confidentiality of the individual data was guaranteed. After signing an informed consent, participants were asked to provide information regarding their sex and age. Then, the rules of the game were explained and participants were encouraged to contact the researcher if any doubts would arise. Participants were taken in groups of two at a time to a designated room, rotating partners after each session. At the end, participants were thanked for their collaboration, received a movie ticket for participating in the study, and were debriefed. The entire experiment took approximately 45 minutes to complete.

Video recordings of the game play sessions were taken and analyzed using the Observer XT®[53, 70]. This specialized software allowed the assessment of the behavioral interactions based on our coding scheme, by registering the timing, duration, and the addressee (i.e., the target player to whom the behavior was addressed) of each interaction. The final coding scheme was composed of 47 behaviors, organized in different dimensions, mostly based on Bales' IPA [7]. The coding scheme was defined before any observation was coded. Each session was coded separately for each human participant integrating the group. Observational coding followed the guidelines for observational analysis [6, 17]. For each behavioral observation, we identified the participant and the addressee (i.e., the target of each behavior), and the correspondent role attributed to the addressee (i.e., partner or opponent). A total of 186 individual observations were coded. A primary coder coded all the data, and two second coders double coded one third of the total number of observations as suggested by standard practice [17], allowing the assessment of the agreement. These sample observations for agreement were selected at random. Overall, the primary coder took approximately 558 hours to code all behaviors, with an average of three hours per individual observation. This number applies to the full coding scheme, which included a broad list of behaviors that falls out of the scope of this paper. Agreement rates were also calculated considering all the behaviors included in the coding scheme, by comparing both the frequency and sequence of behaviors within a two-second-tolerance interval. Overall, the inter-coder agreement was very high, indicating an excellent agreement according to the statistical standards [6, 24]: it ranged from 82.82% to 98.07% of agreement (M = 92.51). Moreover, an optimal inter-rater reliability was also obtained across all of the dependent variables, as indicated

Table 1: Planned contrasts for the Rate of Gaze and of Socioemotional Support Behaviors as a function of the Addressees Role

Comparisons	Planned contrasts	Rate of Gaze Behaviors			Rate of Support Behaviors		
		t	*p*	Interpretation	*t*	*p*	Interpretation
Partners	1. Partner Human vs. Partner Emys-	0.99	.328	Hum≅Emys-	9.05	<.001	Hum>Emys-
	2. Partner Human vs. Partner Glin+	4.78	<.001	Hum<Glin+	7.04	<.001	Hum>Glin+
	3. Partner Emys- vs. Partner Glin+	9.51	<.001	Emys-<Glin+	1.31	.199	Emys-≅Glin+
Opponents	4. Oppon. Human vs. Oppon. Emys-	4.05	<.001	Hum<Emys-	24.96	<.001	Hum>Emys-
	5. Oppon. Human vs. Oppon. Glin+	0.65	.523	Hum≅Glin+	22.03	<.001	Hum>Glin+
	6. Oppon. Emys- vs. Oppon. Glin+	5.10	<.001	Emys->Glin+	5.38	<.001	Emys->Glin+
Partner vs. Opponent	7. Human: Partner vs. Oppon.	0.98	.337	Partner≅Oppon.	6.07	<.001	Partner>Oppon.
	8. Emys-: Partner vs. Oppon.	4.96	<.001	Partner<Oppon.	4.09	<.001	Partner>Oppon.
	9. Glin+: Partner vs. Oppon.	8.74	<.001	Partner>Oppon.	7.90	<.001	Partner>Oppon.

by Kappa = .92 (Kappa max. = .98), the most used statistical index for observational agreement [6, 24].

5 RESULTS

Multilevel Modeling (MLM) was conducted to account for the non-independence of the dyad human members in each group. By following the recommendations of using MLM applied to small groups [39, 40], we used restricted maximum likelihood estimation. Two models were estimated for the dependent behavior (rate of gaze and of support behavior). Rates were obtained by dividing the total number of occurrences of the target behaviors by the total session duration (in minutes) in which those behaviors occurred. In both models the role displayed by the addressee (partner or opponent) was the predictor variable. Because the 2 dyad human members of each group were considered indistinguishable (i.e., they were not differentiated within the dyad on the basis of any characteristics, such as status, age, gender, that could affect the outcomes) the members scores in each dyad were averaged across conditions. In addition, the non-independence was handled by treating the 9 Human-robot interactions as a repeated measure (i.e., 3 sessions X 3 addressees). Unstructured Covariance (UN) matrix was chosen to allow for the correlations and the variances between the 9 interactions to be different by not imposing any constraints on these values. Planned contrasts were conducted within the same MLM analysis to compare the rate of responding towards the addressee displaying the role of partner or of opponent. With these analysis we were able to test how the participants interacted with the robots in this particular social context. To reduce the chance of type I errors, Bonferroni adjustments to the P values were applied, by dividing the critical P value of .05 by the 18 statistical test conducted. Thus, comparisons will be considered statistically significant only if $p<.002$. Results are summarized in Table 1. Average rates of behaviors for each dependent variable are displayed in fig. 3. In this figure, the error bars represent the standard error of the mean.

5.1 Eye Gaze

The MLM for the rate of gaze behaviors yielded a significant effect of the addressee's role, $F(5, 29)= 27.53$, $p<.001$. Results of the planned contrasts towards partners have shown that participants looked significantly more often at the relational Glin+ when it was their partner than at the competitive Emys- or at the human as partners, both $p<.001$.

In contrast, the comparison of gaze towards opponents have indicated that participants looked more often at Emys- when it was their opponent than at Glin+ or at the human when they were opponents, both $p<.001$. Also relevant were the analysis comparing the rate of gaze behavior towards partners vs. opponents for each target player. These analysis indicated that participants looked more often at the relational Glin+ when it was a partner than when it was an opponent, $p<.001$; while the opposite occurred in relation to the competitive Emys-: participants looked significantly more often at Emys- when it was an opponent than when it displayed the role of partner in the game, p=.001 (see Table 1 and fig. 3a).

5.2 Socioemotional Support

As mentioned above, the expression of socioemotional support included behaviors such as solidarity, raising the other players status, providing help, displaying satisfaction, and rewarding the other players. The results are explained below:

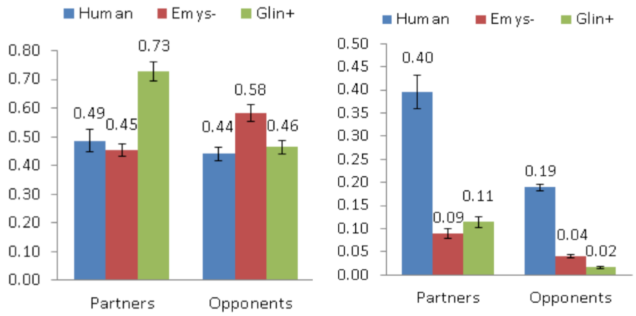
Solidarity was the most frequent manifestation of support amongst our groups of players. These behaviors were displayed in several occasions by all participants in relation to both partners and opponents in the three sessions.

Providing help was the second most frequent behavior of socioemotional support, and it was expressed in at least one occasion by 88.3% of participants. However, it was only observed towards the human player, both as partner and opponent.

Raising the other players' status was less frequent than solidarity and providing help, but it was still displayed by 61.7% of participants in at least one occasion, and it was manifested towards all players, except in relation to Emys- when participants had the human as a partner.

Rewarding the other players was the less frequent behavior. It was mainly observed towards the participants' partner (human and robots), but it was displayed by only 45% of participants.

Based on Bales' model [7], these four types of behaviors were then aggregated in the category of socioemotional support. The number of occurrences, divided by the total duration of the session in which the behaviors were displayed, was further analyzed with MLM analysis. This analysis yielded a significant main effect of the addressee role, $F(5, 29) = 132.22$, $p<.001$. Results for the 9 planned comparisons indicated that *participants provided significantly more support to the human than to robots in both role conditions (i.e., human as a partner or as an opponent)*, compared to the support given



(a) Rate of Gaze Behavior

(b) Rate of Support Behavior

Figure 3: Mean Rates of Support and Gaze Behaviors as a function of Player's Role. Rate of behaviors was calculated by dividing the number of behaviors by the total duration of the session. Error bars represent the standard error of the mean.

to robots. The support provided to the relational Glin+, in comparison to the competitive Emys-, when each displayed the role of partner, was not statistically different, p=.199; however, *participants responded differently to the robots when they were opponents, by providing more support to the competitive Emys- than to the relational Glin+ when they were its' opponents* in the game (see fig. 3b), p<.001. Consistent with our hypothesis, comparisons based on the role each addressee played (partner or opponent) have shown that *a higher frequency of support towards partners than towards opponents occurred for each addressee player*, all p<.001 (See Table 1 and fig. 3).

6 DISCUSSION AND CONCLUSION

In this paper, HRI in small groups were studied by focusing on two key aspects of interpersonal communication: *eye gaze* and displays of *socioemotional support* during a face-to-face game play activity. We investigated the frequency and directionality of these behaviors, taking into account their roles (partners and opponents) and also the goal orientation of the robot (competitive vs. relational-driven).

Regarding rate of gaze, participants looked more often at the cooperative Glin+ when it played the role of a partner than when it was an opponent, and more often at Emys- when it played the role of opponent than the role of partner. These results favoring the cooperative Glin+ as a partner are in line with previous research suggesting that gaze is an important binding factor among ingroup members, contributing to their cohesion and to build interpersonal relationships [10]. Thus, it is understandable that these behaviors were more often directed at the relationship-driven Glin+, since it displayed more cooperative and positive social traits than Emys- when both displayed the role of partners. In contrast, the gaze favoring Emys- as an opponent could be related to its' competitive traits, which might have been perceived by participants as a threat to their goals. This interpretation is consistent with previous studies showing that people tend to inspect threatening targets more often than nonthreatening, as a way of monitoring, seek information, and have a higher sense of control (e.g., [2, 26, 64]). Thus, the higher frequency of gaze towards the competitive Emys- could have occurred as a way to collect more information from and to deal with this rival more efficiently. Consistent with this perspective, previous studies have also shown that gaze frequency is an important index of monitoring function and information seeking in competitive situations (e.g., [26]).

Moreover, gaze responses favoring the competitive Emys- instead of the relational Glin+ were only found when they were opponents, a result similar to the findings for support behaviors, which also occurred more frequently towards the opponent Emys- than to the opponent Glin+. In our view, this last result is intriguing, as it goes against our initial prediction that socioemotional support would be preferentially targeted at the relational Glin+ (in comparison with the competitive Emys-), regardless of its' roles. In fact, we expected that Glin+ would be more likely to elicit these behaviors in return since relational-oriented behaviors tend to foster affiliation, cooperation, and support (e.g., [23]), whereas competitive gaming strategies tend to elicit antagonism, rivalry, aggression, and undermine pro-social motivation (e.g., [60]). Possible interpretations for these different behaviors towards the two robots displaying the role of opponents may rely not only in the need of participants to monitor (with gaze behavior), but possibly to also appease the competitive Emys-. A need that they might have not felt in relation to Glin+, when it was their opponent, because of its' relational traits. Nevertheless, further research needs to be conducted with competitive versus relational robots and these interpretations would benefit of being addressed using other complementary measures. Consistent with our hypothesis, was also the finding that support behaviors occurred more frequently towards the partner, instead of towards the opponents. These results are consistent with prior studies showing that people tend to express more positive feelings and support toward members of the perceived ingroup [63]. Also consistent with our initial predictions is the observed higher frequency of support towards the other human player. This finding is also consistent with prior results observed in the context of group membership preferences [9], and studies that indicate the existence of a higher preference of positive social exchanges towards members perceived as being more similar to themselves [33, 35]. Another possibility is a higher sense of discomfort or lack of perceived likable traits in robots, as previous studies have shown [15]. However, the results for gaze behavior displayed towards humans were relatively similar in both roles (partner or opponent).

Also important was the use of Bales' IPA guidelines to code each single behavior within one of the 12 subcategories that are used to evaluate the social dynamics in small groups. We chose to code each single behavior of the socioemotional support dimension, in addition to gaze, to have a deeper understanding of how the interactions occurred in this dimension. This microanalysis allowed us to find that, with the exception of rewarding other players, behaviors such as solidarity, raise the other players' status, and helping were expressed by the majority. Solidarity, for example, was displayed by all participants, was the most frequent behavior in this category, and it was directed towards all players in the three sessions. In our view, these results are very important, as they show how humans can collaborate and express solidarity and other manifestations of positive affect in mixed groups, towards both robots and humans. However, the remaining behaviors were neither expressed towards all the other players nor in all sessions. For example, reward others was the least expressed by participants. This particular behavior typically occurs in response to negative situations [7], as it is the case of antagonism among group members or specific occurrences of disagreements, which are a different type of positive behaviors when compared to manifestations of solidarity, helping, or raising the other player status.

Also relevant, was the fact that behaviors aiming at providing help to another player only occurred towards humans, regardless of their role. This result might have been due to the setting of the game itself. Because only the human players were in charge of tasks such as shuffling the cards and dividing them among players, only they could provide help in doing so. This happened because both robots do not have a physical set up (i.e., robotic arms) to perform these tasks. Given that most of these behaviors were of non-verbal nature, this supports the idea that they occurred mainly in occasions where subjects had to physically *do something*, and therefore this seems like a likely scenario to explain the lack of behaviors of this sort directed to Emys- and Glin+. This is an important point to consider when developing HRI scenarios that require some form of physical cooperation among players. Other limitation was the duration of the sessions. Although playing cards with a robot tend to be perceived as a novel and engaging task, the total duration of the HRI and the amount of games played might have caused participants fatigue, which may have resulted in a faded interest across sessions. Furthermore, despite the fact that limitations of Bales' IPA have already been discussed elsewhere [30], it is still important to acknowledge them and underline that these were taken into account during the construction of the coding scheme, by embedding into it a set of specified variables that allowed a better understanding of the interactions, both regarding their addressee but also regarding the general form and purpose. The use of observational methods also presents important advantages [6]. However, the combination of multiple methods and measures, can offer a better approach to study the same phenomenon by reducing the limitations of one method and increasing the accuracy and validity of the findings [36]. Nevertheless, the present study adds useful insights to a growing body of researchers and users that are interested in studying interactions between multiple robots and multiple users in small groups interactions.

7 FUTURE ENDEAVORS

The use of autonomous robots in the context of small mixed groups to study the frequency of gaze and socioemotional behaviors is in its own right, an interesting avenue of research. Yet, this was performed as part of a contextualized effort to create a data-driven understanding of how humans, in general, respond to important characteristics of social group interaction displayed by robots. Such findings are important to consider when designing social robots and are of particular usefulness, not only in situations where humans and robots might have to compete with one another, but also in situations that demand some degree of cooperation between them. Because both gaze and displays of socioemotional support are both product of interaction among subjects (instead of simple individual responses), it is important to consider how to shape these interactions in order to make them acceptable for humans.

From the context of psychological research, we can assume that the preferences of interaction, or choices of preferential targets are related to the addressers' own perception, personality, background, motivations or familiarity. In this context, our study contributes with similar insights to the HRI field, in particular by exploring mixed-groups of humans and robots. Humans develop mental models about others, that allow them to explain and predict other people' behavior and to make assumptions about their intentions. In complex interaction settings, especially those involving technological artifacts, the correct transmission of this type of information (i.e. goal orientation) is crucial to the development of an optimized interaction process. This will allow robots to behave appropriately when establishing relationships with people [12]. In this paper, we focused on two specific types of relationships using the criteria of goal orientation, i.e. competitive and cooperative orientation. Our findings are useful for the purpose of designing robots that might have to act as partners or opponents, in small group situation, as an optimal robot design should consider effective ways to convey internal states and goal orientations (either by the physical aspect or through continual feedback) that complement information given by the robot' cognitive abilities (for a discussion of the use of this term, see [58] , through emotional and goal-oriented information that might play a regulatory effect [12]). Nevertheless, future research should also analyze other factors influencing these interactions, e.g., task and performance-related variables, which are known to affect team-membership preferences.

The results of this study demonstrate a clear preference of interaction towards the human player, which may be caused by some form of ingroup bias towards the human, or of a sense of discomfort or lack of perceived likable traits displayed by the robots. This evidence fosters the urge to understand and improve the way humans and robots interact in order for them to establish effective collaborations.

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