Interaction-Shaping Robotics: Robots That Influence Interactions between Other Agents

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Work in Human–Robot Interaction (HRI) has investigated interactions between one human and one robot as well as human–robot group interactions. Yet the field lacks a clear definition and understanding of the influence a robot can exert on interactions between other group members (e.g., human-to-human). In this article, we define Interaction-Shaping Robotics (ISR), a subfield of HRI that investigates robots that influence the behaviors and attitudes exchanged between two (or more) other agents. We highlight key factors of interaction-shaping robots that include the role of the robot, the robot-shaping outcome, the form of robot influence, the type of robot communication, and the timeline of the robot's influence. We also describe three distinct structures of human–robot groups to highlight the potential of ISR in different group compositions and discuss targets for a robot's interaction-shaping behavior. Finally, we propose areas of opportunity and challenges for future research in ISR.

CCS Concepts: • **Human-centered computing → Collaborative and social computing theory, concepts and paradigms**; • **Social and professional topics** → *Computing / technology policy*;;

Additional Key Words and Phrases: Human–robot interaction, multiparty interactions, social influence, shaping interactions, interaction-shaping robotics

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1 INTRODUCTION

As the field of Human–Robot Interaction (HRI) continues to grow, researchers are designing and studying increasingly complex human–robot social interactions, including those that involve

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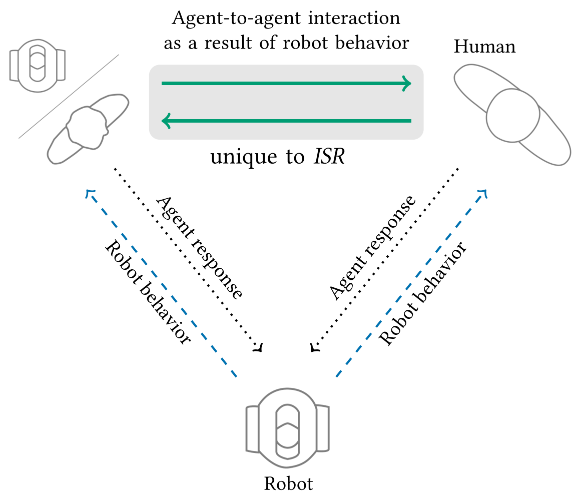


Fig. 1. Schematic depicting an interaction-shaping robot that displays behavior (blue dashed arrows) toward two other agents: one human and one human or robot. The agents may (1) respond reciprocally toward the robot (black dotted arrows) and/or (2) change their interactions with one another as a result of the robot's behavior (green bold arrows). We consider this latter effect to be unique to interaction-shaping robots.

multiple people and/or multiple robots [29, 106, 111]. Numerous studies examining human–robot group interactions have demonstrated that robots can do more than influence one person's behavior. Robots can also shape current and subsequent interactions between multiple agents, especially including those between people [42, 103, 120, 126].

This article proposes a new research area—Interaction-Shaping Robotics (ISR)—which we define as the study of robots that influence the behaviors and attitudes exchanged between two (or more) other agents. Figure 1 illustrates this definition. The figure represents the robot's behavior toward two other interactants with blue dashed arrows. One of the interactants in the diagram is a human and the other may either be a human or a robot. The robot's behavior can then result in two possible effects: (1) a direct reciprocal effect from the agent (black dotted arrows) and/or (2) an indirect effect of the robot's behavior on the interaction of the other interactants (green bold arrows). This first direct reciprocal effect is characteristic of traditional HRI research spanning both dyadic and multiparty scenarios, where a robot's behavior shapes human behaviors and attitudes back toward the robot. This second indirect effect of the robot's behavior on the interactions between other agents is unique to ISR, where a robot influences how one agent behaves toward and/or thinks about another interactant in a group. While some researchers explicitly design their robots to shape interactions between other agents [29, 30, 44, 120, 132], many robots also produce interaction-shaping effects that are neither designed nor intended by the robot or researcher. ISR represents a critically needed addition to the current topic areas covered in the HRI community, as it invites researchers and practitioners to be more deliberate and thoughtful about the potential of influencing interactions when designing and deploying robots, especially considering how these interactions between other agents may be negative or positive, intended or unintended.

To illustrate an example of an interaction-shaping robot, consider the humanoid robot that made vulnerable expressions in a collaborative game with three people [120]. In response to the robot's vulnerable expressions (e.g., "I sometimes find myself getting a bit discouraged..."), some human team members verbally responded to the robot, which are examples of direct responses to the robot's behavior (black dotted arrows in Figure 1). Later in the collaborative game, people were more likely to explain their mistakes to their human team members if their robot teammate had made vulnerable utterances, as opposed to neutral utterances [120]. This increased likelihood to explain their mistakes to fellow human team members displays how the robot shaped the interactions between its human teammates (green bold arrows in Figure 1) by influencing what information these human team members shared with each other. Beyond this one example, other work in HRI has also demonstrated a variety of interaction-shaping robots, including robots that influence the amount of time people spend talking to one another [44, 77, 97, 129] and backchanneling [105, 126], robots that change how people in a group perceive [63] and resolve [108] conflicts, robots that shape people's perceptions of group dynamics such as inclusion [119] and cohesion [112], and robots that influence how people behave toward other robots [29].

In this article, we present ISR as a subfield of HRI to bring this research area to the attention of the HRI community and align researchers whose work touches on this space. We define five key factors that characterize the distinct methods that interaction-shaping robots use to influence interactions between other agents. We do not claim that the presented key factors represent a complete and sufficient theoretical framework but suggest that these factors support our understanding of the impact interaction-shaping robots have in society and highlight unexplored research directions and possible ethical risks in developing interaction-shaping robots. Additionally, we describe three categories of human–robot group structures, along with example scenarios within each that highlight distinct opportunities and effects of a robot's interaction-shaping behavior capturing the variation in possible group compositions and targets for interaction-shaping.

To provide a holistic HRI perspective, we highlight ethical, methodological, and computational challenges that arise when building and deploying interaction-shaping robots. Our goal is to inspire future research to carefully consider the ethical risks (e.g., of deception or biased behavior) while recognizing the potential benefits of deliberately influencing human–robot and human–human interactions. Furthermore, we emphasize the need for future research to develop new methodologies for meaningful comparisons between robots, robot behaviors, and scenarios in ISR. By discussing computational challenges, we encourage bridging the gap between related research fields, such as affective computing and network analysis, necessary for developing effective, ethical, and adaptive interaction-shaping robots.

2 BACKGROUND

This section highlights prior work that informs ISR. First, we summarize work on multiparty HRI and the formation of human–robot relationships. Then, we review related work in psychology and sociology that examines how people can shape the behavior and attitudes of other people.

2.1 Human–Robot Multiparty Interactions

ISR is closely related to multi-party HRI. When multiple humans and/or robots interact simultaneously, the scenario is broadly a multi-party interaction. When a multi-party interaction also involves a robot influencing how one agent behaves toward and thinks about another interactant in the group, then the scenario represents both a multi-party HRI scenario and an ISR scenario.

There is a long history of work in multi-party human–robot interaction that motivates ISR. For instance, HRI research in public environments has investigated robot interactions with many people in places like museums [37, 80, 115, 128], office buildings [16, 50], airports [130], train stations [51], hospitals [76], hotels [26], and schools or care centers for children [64, 65, 71, 148]. Recently, there has also been increased interest in studying group human–robot interactions [104, 106], including situations where robots are peripheral companions to groups [55, 126] and situations where robots directly participate in conversational engagements [42, 75, 77, 93, 129, 135], multi-party games [31, 113, 136, 138], or collaborative tasks [29, 62, 63].

While not all these examples focus explicitly on ISR, several of these research directions have motivated studying how robots can influence human behavior toward other interactants. For example, Kanda et al. [64] describe the deployment of Robovie in a school environment. In this setting, 63% of first-grader's interaction time with the robot was in the company of one or more friends. These types of interactions provide opportunities for robots to shape relationships. Also, Yamaji et al. [148] studied children's interaction with Sociable Trash Boxes (STBs). When the STBs moved individually, only 30% of children in the public environment where the robots were deployed helped with trash collection. Meanwhile, when the STBs moved in groups, 70% of children helped with the trash collection. This group effect could be seen as an example of ISR whereby the behavior of a Sociable Trash Box motivated children to interact with another nearby STB in which they deposited trash. We generally see ISR as overlapping with multi-party HRI, because a subset of ISR requires multiple colocated interactants but focuses more narrowly on how a robot can shape interpersonal processes among other interactants.

A growing body of work in multi-party HRI has started to explore the benefits and risks of interaction-shaping robot. For example, robots using non-verbal behaviors can assist a group conversation by balancing engagement [126] or participation [42]. In addition, robots can help to resolve situations of conflict [63, 108], build more trustful relationships in peer groups [14, 120], enhance the interaction among intergenerational groups [113], influence how included people feel in a group [44, 119], and improve interpersonal interactions [36, 95]. Recent pioneering work has also started to uncover the negative effects robots can have on interactions and the consecutive formation or destruction of relationships. For example, in a scenario where only one team member could ask a robot for information, that team member experienced a greater sense of exclusion from the human members of their group [119]. Also, non-anthropomorphic robots have been shown capable of inducing feelings of ostracism [35] in people, which can also shape subsequent human–human interactions [34]. These examples of interaction-shaping robots in multiparty HRI demonstrate the variety of interaction-shaping effects, both positive and negative, robots can have in a range of multiparty interaction settings.

2.2 Human Relationships with Robots

In addition to shaping human–human interactions, interaction-shaping robots may increasingly form and change human–robot interactions and relationships. Several studies have described the formation of relationships between humans and robots, which grow and develop over a series of interactions. Sung et al. [121] found that robot vacuum cleaner owners build an intimate attachment to their robot vacuum cleaners. Further, soldiers working with bomb-disposal robots have been found to form close bonds with these robots [20]. Similarly, dismantling ceremonies for Aibo robots in Buddist temples in Japan are indicative of close bonds and relationships between owners and their robots [19, 90]. While human–human relationships display a mutuality and depth that human–robot relationships have yet to realize, robots are increasingly incorporating methods to personalize their interactions with people [101], which is a step toward building relationships. As human–robot interactions and relationships become increasingly common, it is important to consider the potential for third-party robots to influence human–robot interactions and relationships, a potential we discuss further in this work.

2.3 Human-to-Human Social Influence

How people can shape the behaviors and attitudes of other people through social behavior is important for ISR, since robots can potentially use similar methods of social influence to shape the interactions between other agents. Social influence is typically studied in the field of social psychology. The literature broadly studies aspects of conformity, obedience and power, attitudes, group processes, and effects of culture and gender concerning social influence [7, 56, 66, 78]. We would like to note that in this section, we focus on social influence a human or robot could exert knowingly, e.g., through language or behavior. In the following paragraphs, we discuss phenomena from the human-to-human social influence literature that we found particularly promising for HRI or that have been used in previous HRI studies. We recommend the interested reader to consult a social psychology textbook [7, 56, 66, 78] for an exhaustive literature review on social influence. One way people can exert social influence is by their behavior or emotion spreading from one person to another through social interactions, an effect known as behavioral or emotional contagion [11, 24, 25]. A variety of behaviors have been found to spread from person to person including selfish behaviors in economic games [61] or aggressive behavior in children [33]. Emotions are also contagious, for example, people are more likely to be happy if they are in contact with others who are happy [41] or become depressed if they are assigned to live with a mildly depressed roommate [59]. Emotions can also spread from one person to an entire group, for example, Barsade [11] demonstrated that one person's positive affect in a collaborative group led to improved cooperation between group members, less conflict, and increased perceived task performance.

In addition to behavioral and emotional contagion, people can influence the behavior and attitudes of other people using other forms of social influence. For example, people change their behavior to match the behavior of others, an effect known as conformity [27]. Famously, Asch [8] demonstrated that participants asked to judge the length of the line would choose a clearly incorrect answer about 37% of the time if their peers also chose the same incorrect answer, displaying the powerful effect of conformity and peer pressure. Compliance is another type of social influence and refers to cases where a person acquiesces to the request of another person (e.g., purchasing items from a door-to-door salesman, voting for a political candidate touted by a colleague) [28]. In addition to conformity and compliance, people are also greatly influenced by social norms—rules about actions to perform or avoid that are upheld by a community of people who follow and enforce them [13, 18]. Examples of social norms include shaking someone's hand when meeting them, not littering in a park, and speaking softly in a library.

In addition to individual behaviors, group-level social influences such as intergroup processes and balance theory can shape people's behaviors and attitudes. Intergroup effects in form of biases describe the natural favoring of one's own group (ingroup) over other groups (outgroup). This ingroup-outgroup bias results in implicit intergroup and cognitive biases to the detriment of the perception of and behaviors toward the outgroup [40]. To overcome those ingroup-outgroup biases, the literature proposes the contact hypothesis that suggests that relationships between groups can be improved through positive contact in a joint interaction [5, 147]. Balance theory suggests that groups naturally strive for a balanced state, meaning that attraction relations are reciprocal [52]. If imbalances occur, then the balance can be restored by changes in the individual or interpersonal changes. For example, one person disliking another can change their opinion if they realize that the other group member likes them. However, a group member can also change their opinion from liking to disliking the other, which can cause ostracism [125].

This section offers a brief overview of the literature that covers aspects of human–human social influence and intergroup effects, demonstrating that people's behaviors and attitudes are strongly influenced by the people around them and their behavior. As people increasingly interact with social robots, they will also inevitably influence the behaviors and attitudes of these people, likely in similar ways (e.g., contagion, conformity, and compliance) as in human–human social influence. As a result, effects found in human–human literature offer promising directions for studying interaction-shaping robots.

Table 1. Key Factors of Interaction-Shaping Robots. The ISR Factors on the Left Distinctly Identify Mechanisms that Allow Robots to Shape Interactions Between Other Agents

ISR Factor	Category	Description
Role of the Robot	Guiding Facilitator	The robot leads and directly mediates the interaction between the agents.
	Peripheral Facilitator	The robot is present and active, but is not directly involved in the interaction.
	Peer Group Member	The robot acts as a peer relative to the agents.
	Specialized Group Member	The robot adopts a special role as a group member relative to the agents.
Robot-Shaping Outcome	Cognitive	The shaping outcome is measurable in changes in cognitive attitudes and thoughts (e.g., interpersonal evaluation, feelings, intentions).
	Behavioral	The shaping outcome is measurable as a change in behavior (e.g., spatial repositioning, amount of speaking, gazing).
Form of Robot Influence	Explicit Robot Influence	The robot addresses aspects of the interaction explicitly through clear and exact communication, directly prompting or requesting a change in the interaction (e.g. calls a conflict out and asks for resolving it).
	Implicit Robot Influence	The robot implicitly addresses aspects of the interaction that could lead to a change in the interaction among the other agents.
Type of Robot Communication	Verbal	The robot uses verbal natural language to shape the interaction.
	Non-Verbal	The robot uses non-verbal behavior (e.g., gestures, gaze, movement, resource distribution) to shape the interaction.
Timeline of Robot Influence	Immediate Influence	The robot's behavior immediately shapes the interaction between the agents.
	Long-Lasting Influence	The robot's behavior shapes the interaction between the agents after the robot's interaction-shaping behavior has concluded (e.g., the following day).

3 FACTORS OF INTERACTION-SHAPING ROBOTICS

This section presents key aspects for Interaction-Shaping Robotics as five factors that greatly influence how a robot shapes interactions (see Table 1). To develop these factors, we consulted recently published surveys on group HRI [45, 104, 106] and reviewed the surveyed and more recently published literature. Based on prominent examples from the literature, we discussed distinguishing elements repeatedly among all authors, drafted definitions and naming of the factors, and refined them while mapping works to factors and their categories. Before agreeing on the final five factors, we focused on the overall clarity to a potential reader and the fit of work from the literature. The result of this process is documented in the remainder of this section, in which we describe and exemplify each factor with related work from the HRI community.

The following subsections describe factors that we identified as uniquely relevant and essential for ISR: (1) the role of the robot in the group, (2) the robot-shaping outcome, (3) the form of robot influence, (4) the type of robot communication, and (5) the timeline of robot influence on the interaction(s). Similarly to the broader field of HRI, we acknowledge that many factors other than these five may influence ISR interactions [39], including robot-specific factors (e.g., physical appearance [89], anthropomorphism [151]) and individual differences in human interaction partners (e.g., personality, prior familiarity). While these additional factors can certainly influence ISR interactions considerably, the five factors we have chosen to focus on reflect aspects that have a unique and sizable impact on how robots can shape interactions between other agents.

Similarly to work in the field of HRI more broadly, we also expect that some interaction-shaping factors will have similar effects when they are expressed by a robot compared with when they are expressed by a human (e.g., expressions of vulnerability being reciprocated by others [120]). However, the literature shows that effects might not always replicate, as in the case of replicating the effects of Asch's conformity experiment [17, 109] or have an effect with reduced magnitude when compared to human–human interactions [99]. Additionally, robots can adopt some interaction-shaping behaviors that are similar to those that people can express but they can also shape interactions in unique ways by, for example, expressing lights, sounds, and movements impossible for humans. The five interaction-shaping factors we identified represent ways that robots can influence other agents that contain similarities with human–human interaction-shaping and key differences.

3.1 Role of the Robot

The role that a robot adopts in human–robot interactions has a significant impact on how people perceive the robot and respond to its behavior. Interaction-shaping robots in prior work have often adopted the roles of *facilitator* or *group member*, which offer particular opportunities but also challenges when shaping interactions. Some types of interactions, like role-playing games [136], allow robots to switch between the facilitator and group member roles.

Guiding Facilitator: When an interaction-shaping robot adopts a guiding facilitator role, it directly leads the interaction between the other agents. A robot can utilize this role to explicitly draw the agents' attention to the aspects of the interaction the robot wants to shape. For example, Shen et al. [108] showed how a Keepon robot can help children to resolve their resource conflicts by explicitly pointing at the conflict and suggesting to focus on a constructive solution. In addition, Birmingham et al. [14] exemplified how a robot could guide a support group session for stressed students with questions and self-disclosure statements to invite students to share their stress experiences and improve trust between participants. As long as the robot is accepted as the leader, it can effectively guide the group, like eliciting participation from quiet individuals when making hiring decisions [107], or encouraging deeper conversations among strangers [149]. Engagement from other interactants is crucial for robots in this role.

Peripheral Facilitator: An interaction-shaping robot can also facilitate an interaction between agents from the periphery. The robot is present and active, but it is not directly involved in the main task being carried out by the group. For example, Tennent et al. [126] explored this role for a microphone-shaped robot, MicBot. During human group conversations, MicBot followed the speaker and attempted to encourage the least talkative participant to take the floor of the conversation by turning toward them. The authors found that these behaviors led to a more balanced engagement of all group members [126]. In another example, a Cozmo robot used similar behaviors to turn toward children to follow their play, encourage participation, and prompt collaboration to help the process of inclusion among children [44]. These examples demonstrate that peripheral robot facilitators can have a profound impact on an interaction even though engagement from other interactants with the robot is not a requirement. It is important, though, that the robot's actions are recognizable enough for people to not forget about the robot or ignore it [95].

Peer Group Members: Interaction-shaping robots can also take on the role of a peer, similar in function to the other group members. In contrast to the facilitator role, the robot can leverage the establishment of group membership to shape interactions, e.g, leading to higher trust by the other group members [10]. One context where prior work has explored interaction-shaping robots as peers is in collaborative task and game contexts, where the interaction-shaping behavior is embedded within the task or game. For example, Strohkorb Sebo et al. [120] found that a robot that admitted having made mistakes during the game play could increase the number of vulnerable statements made by other people within the group.

Specialized Group Members: An interaction-shaping robot can also fulfill a special role as a group member, where the robot makes a unique contribution to the group but still benefits from emerging group membership. For example, Mutlu et al. [77] studied interactions with a travel agent robot that gave people advice on travel destinations. Because the robot's goal was to help people select a suitable travel location, the robot's primary role (serving as an information source) was distinct from the role of other group members (seeking advice). A robot's special role might thereby offer the robot opportunities for shaping interactions that can be part of the role itself or the task-based behavior. In other examples from prior work, robots have adopted a variety of special roles including an information source in a desert survival task [119], a 'bomb scanner' in a bomb defusal game [63], and a guesser in a word guessing game [42].

3.2 Robot-Shaping Outcome

A robot shaping an interaction might lead to *cognitive* and/or *behavioral* outcomes. Cognitive outcomes typically result in a change in cognitive attitudes often measured through questionnaires or dedicated tasks, e.g., the Implicit Association Test (see Reference [54] for an example). Behavioral outcomes can typically be measured within the interaction between the robot and other agents or in dedicated tasks. Changes in cognitive attitudes may often influence changes in behavioral outcomes. However, it is also possible for people to change their behavior while their cognitive attitudes remain the same, e.g., a requested spatial repositioning might not change how the other agents perceive themselves or the interaction.

Cognitive: Cognitive outcomes are measurable changes, e.g., in interpersonal attitudes, changes in trust between the other agents, or aspects of group dynamics such as cohesion or perception of group identity. For example, researchers explored a non-anthropomorphic robot's leaning gestures and their influence on interpersonal evaluations in conversations [95]. In another example, researchers address intergroup effects through explicit experimental manipulation before the interaction with the robot, and through an implicit manipulation by giving one group member the unique role of the robot liaison. They find that the role of the robot liaison has a stronger effect on perceived inclusion than the explicit formation of ingroup and outgroup before the interaction with the robot [119]. Other works explore the effect of robot exclusion, inclusion and overinclusion on the experience of ostracism [35], the perception of inclusion in groups of mixed visual abilities [79], or trust in support groups [14]. A change in stereotypical thinking as demonstrated by Hitron et al. [54] can also be understood as a cognitive robot-shaping outcome that generally influences how an individual thinks and acts toward others in society.

Behavioral: Robots can also influence how other agents, individually or as a group, behave in interaction-shaping scenarios, including how much time agents spend speaking, how group members communicate with each other, work as a team, or how they change their spatial positioning [15]. Prior work has provided multiple examples that have demonstrated that participants' speaking behavior can be altered by a robot's shaping behavior [42, 77, 79, 86, 114]. Other works demonstrated that robots can change conflict resolution strategies around toys among children [108] or how children play with members from a different group in the context of social inclusion [44]. Further examples include robots that could elicit prosocial interventions in case of robot mistreatment [29], evoke task-based explanations among children [21], alter a group's decision-making process [119], or prompt more trash disposal to a robotic trash can [148].

3.3 Form of Robot Influence

Another important factor of ISR is how the robot influences the interaction among the other agents. We consider two possible forms of robot influence: *explicit* and *implicit*. While this section discusses these two forms as distinct categories, we recognize that the form of robot influence is best described by a spectrum where a specific shaping attempt might fall between explicit and implicit. The form of robot influence might affect people's ability to identify and be aware of the robot's shaping behavior. We discuss the ethical considerations of forms of robot influence in combination with other factors in Section 5.1.

Explicit Robot Influence: A robot can shape interactions explicitly by using behaviors or other means that elicit clear expectations on how the interaction between the other agents should change. Typically, a robot would use direct prompts and requests. For instance, one research study investigated the efficacy of a couple's counselor [133]. The robot invited the couples to explore exercises that aim to improve their communication skills among them. In other research, a robot explicitly asked participants to reposition themselves when interacting with the robot [15]. Another example of the explicit influence that does not use verbal communication is the robot MicBot [126]. In this work, the robot takes the form of a microphone that turns to encourage participants to speak. While Micbot cannot verbally explain its actions, swiveling toward a person does clearly indicate Micbot's desire for that person to speak. Other works explore a robot's explicit influence in situations of resource conflict [108], children collaborating in a rocket-building game [118], or general moderation of a collaborative game [113]. In cases where the robot's influence is explicit, other agents have the choice to either accept the robot's influence or reject the robot's influence. Therefore, the ability of a robot to shape interactions explicitly depends on the decisions of the other agents to follow its prompts.

Implicit Robot Influence: In contrast to shaping interactions in ways that clearly communicate expectations toward the other agents, robots can also implicitly shape interactions. For example, in a word-guessing game, a robot used gaze cues to encourage more participation from a less talkative person [42]. Even though participants might notice irregular patterns in the robot's gaze when asked to reflect on the robot's behavior, the robot does not make it explicitly clear to the participant that its gaze may result in a change in their behavior [43]. Additionally, robot expressions of vulnerability in a game context increased people's likelihood to explain their mistakes to one another and console those who made mistakes [120]. Further research has shown that a robot being unreliable in a task could elicit more task-based explanations among children [21], or could harmonize an interaction, i.e., yielding the floor to a less active group member after taking the floor in a short natural exchange with the current speaker(s) [73]. Implicit means of shaping interactions typically use subconscious responses, like gaze or psychological processes, to influence the interaction. These subconscious responses might though be subject to individual differences between people and could affect how effectively a robot can shape interactions through implicit means.

3.4 Type of Communication

Robots can shape interactions through *verbal* and *non-verbal* communication. Verbal communication involves the use of natural language. Non-verbal communication comprises other expressive forms of behaviors, such as movement, gesture, backchanneling, and gaze. This section describes how these behaviors can contribute to how a robot shapes interactions between other agents. Important to note is that the type of communication only concerns interaction-shaping behaviors. The robot could display additional behaviors intended for other aspects of the interaction that use other types of communication.

Verbal communication: Verbal communication can be used in different ways by robots to shape interactions, e.g., utterances can provide recommendations or mention problematic situations explicitly. For example, Jung et al. [63] studied the effects of a robot with a special role in a shared bomb-defusal task. The robot admonished a confederate for their hostile behavior toward another participant and, through this verbal behavior, called attention to the conflict between the human team members. Robots in guiding facilitator roles, as discussed in Section 3.1, often use verbal communication to shape interactions, acting as a couples counselor [132], reducing conflicts among children [108], and improving the perception of a patient as evaluated from a caregiver's or doctor's perspective [23]. While verbal behavior can be an effective way to shape interactions between agents, a robot's use of verbal behavior may lead people to believe that a robot can both produce and understand natural language. If a robot cannot understand natural language to the same extent that it can produce it, then people's expectations of the robot could be violated [92], and, in turn, this could reduce trust [67] and social influence. Therefore, considering human expectations is particularly important for these interaction-shaping robots.

Non-verbal communication: Non-verbal behaviors typically used by interaction-shaping robots include gestures, movement, backchanneling, gaze and functional interaction-shaping behaviors. Non-verbal communication can help coordinate human–human conversations and group interactions and is influential in human–robot interactions [102]. For example, a robot's gaze behavior can balance human participation in conversations [42], shape conversational roles [77], and distribute speaking turns to less talkative members of a conversation [73, 114]. Furthermore, Erel and colleagues explored the effect of gaze and leaning gestures of the non-anthropomorphic robot, Kip, on the interaction between humans. They found that these behaviors can positively influence the perception of conversation partners [95] and improve perceived emotional support within the group [36]. This work points out one advantage of fully non-verbal robots: users have lower expectations of them. This could facilitate creating effective interaction-shaping robots.

Functional non-verbal behavior can also be used by robots to shape interactions among two other agents. For example, non-humanoid robots "shooting a ball" unequally in a group interaction can raise feelings of exclusion [35]. Additionally, in industrial contexts, a robot arm's unequal distribution of resources has been shown to systematically influence human–human interaction dynamics [62]. Other examples of non-verbal interaction-shaping behaviors include the microphone-shaped robot MicBot that balances engagement [126], the robot Cozmo that encourages active play to improve inclusion among children through body movement, sound and facial expressions [44], and robotic bar-stools that encourage spontaneous conversation [98]. In summary, non-verbal behavior can be designed from human–human communication or following the specific capabilities of the robot, making a robot's possible repertoire of interaction-shaping behaviors both shared and unique relative to those used by people.

3.5 Timeline of Robot Influence

Once a robot has expressed interaction-shaping behavior, the robot's behavior may influence the agents' interactions in both the *short-term* and the *long-term*. A robot's behavior may have immediate interaction-shaping effects on the agents that are physically present with the robot. It is also possible that the robot's interaction-shaping behavior might have long-lasting effects and influence the agents' subsequent interactions with others, even in the absence of the robot's presence.

Immediate Influence: When a robot exhibits interaction-shaping behavior (e.g., gaze cues [42, 77] and supportive comments [105]), often their effects on the agents with whom the robot is interacting are immediate, occurring seconds or minutes after the robot's behavior. Most examples of ISR focus on immediate effects. For example, during one interaction, interaction-shaping robots can lead to more constructive resolution of conflict [108], greater harmony in group conversations [73], more balanced engagement [126] or participation in conversations [42], more vulnerable statements [120] or higher trust among group members [14].

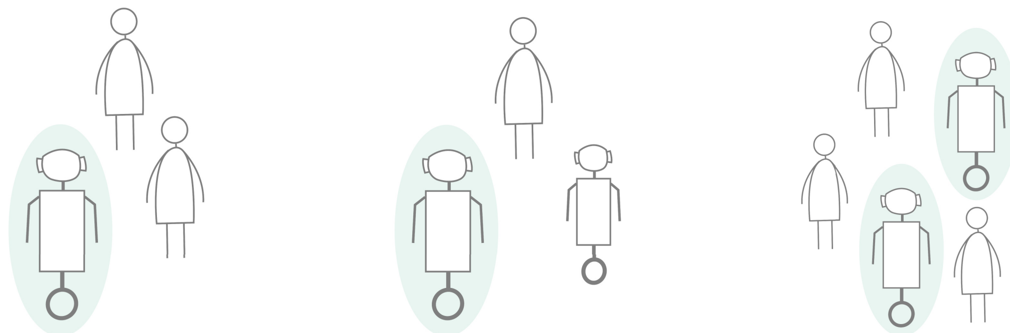
Long-lasting Influence: It is also possible that a robot's behavior shapes interactions that occur after the interaction with the robot took place. These long-lasting effects "carry over" to shape the interaction between multiple agents in subsequent human–agent interactions. For example, Erel et al. [34] studied how the effect of ostracism, induced by multiple robots on one person, influenced the person's subsequent human–human interactions, including their proximity to other people and compliance with an experimenter's request. It is important to note that these long-lasting effects can occur even if not all of the affected agents were present with the robot (the experimenter in Erel et al. [34]) when the robot exhibited its interaction-shaping behavior (the robot ostracizing the human participant in Erel et al. [34]). Another example of an effect that has been found to carry over is prosociality [82]. For example, Shiomi et al. [110] showed that positive feelings from a robot hug could lead to people donating more money to victims of an earthquake. This suggests that long-lasting interaction-shaping robot behaviors have the potential to positively impact human–agent interactions without a dependency on the robot. This is a particularly exciting line of work that would benefit from more research.

4 INTERACTION-SHAPING GROUP STRUCTURES

In this section, we discuss three human–robot group structures (illustrated in Figure 2) that represent distinct interaction-shaping group structures. These group structures characterize different group compositions and thereby give insight into the interactions that a robot might shape (human–human or human–robot) and how many robots (one or more) are acting to influence other agents. Each group structure presents unique opportunities for ISR, which we highlight using examples from related work and by proposing areas of future research.

4.1 Structure I: One Robot Shapes a Human–Human Interaction

Structure I describes a group structure where one robot shapes the interaction between two or more other people (Figure 2(a)). Scenarios investigating this group structure have received the largest amount of attention as researchers have sought to use robots to improve human-to-human interactions and group dynamics. Several robots have been shown to increase the amount and quality of interactions between people, including those between older adults in care facilities [97, 127], teammates [129], and children with autism and their caregivers [103], therapists [68], and playmates [152]. Other robots have been designed to assist people in collaborative contexts, using a variety of behaviors (e.g., gaze [42], mechanical movement [126], and verbal utterances [105]) to encourage more equal participation [42, 105, 126], promote expressions of vulnerability [120], and mediate conflict [63, 108] between human group members.



(a) Structure I (b) Structure II (c) Structure III

Fig. 2. Overview of the three interactions-shaping group structures (Section 4). The relationships-shaping robot(s) are marked with a green ellipse. Relationships are shaped among the remainder of agents.

Since having positive interactions and relationships with other people are critical to our well-being and everyday experiences [91, 134, 142], investigating how robots can positively shape human–human interactions will continue to be an important area of research. For example, for robots that collaborate with people in work teams, it would be helpful for them to contribute positively to the team's dynamics in light of research that has demonstrated the positive influence social team dynamics (e.g., inclusion, trust) have on a team's performance [74, 85]. Other research could further explore how robots can shape other key human–human relationships including long-term romantic partnerships [132], friendships, and caregiver-patient relationships [32] to name a few. In addition to investigating how robots can positively assist human–human interactions, it is also important to explore the negative effects of robots on human–human interactions so that people can be aware of the possible dangers robots pose to human–human interactions and relationships. For example, Sebo et al. [105] showed that giving a human team member a specialized role to interact with the robot significantly reduced how included the human team member felt in the group. With this knowledge, human teams can proactively work to counteract the exclusion a team member may feel if they are given a specialized role to interact with a robot.

4.2 Structure II: One Robot Shapes a Human–Robot Interaction

Structure II pertains to situations where an interaction-shaping robot influences a human–robot interaction between one or more humans and one or more robots (Figure 2(b)). Although limited prior work has investigated scenarios with this group structure, it is likely that it will become common in the future as robots are increasingly incorporated into everyday activities in human environments. For example, we foresee this type of scenario occurring often with service robots, which may need to hand off their interaction with users to another robot due to being unable to complete the desired task (e.g., because of technical issues or limited robot capabilities). For example, Tan et al. [123] demonstrated that a first robot could set human expectations of a second robot, to whom the first robot makes a hand-off, potentially shaping how the human interacts with the second robot. Further, imagine if the first robot told the group that the second robot was malfunctioning in a particular way, setting low expectations over its functionality. Perhaps the user(s) would then be more forgiving to errors by the second robot, showing greater trust recovery [144]. Another example of Scenario II are situations where the way in which a robot interacts with another robot influences how humans perceive the other robot. Söderlund [117] recently provided initial evidence that this type of effect is possible with human initiated robot-to-robot interactions.

Likewise, we suspect that it could emerge in robot-initiated robot-to-robot interactions [51] in multi-party HRI.

In the future, interaction-shaping robots could influence human–robot interactions in a fully reciprocal manner. That is, interaction-shaping robots could influence both how humans interact with other robots and their attitudes toward them, as in the prior examples, and how these other robots interact with humans. This would require future social robots to better perceive changes in behavior and attitudes as well as better process information provided by other robots about users. Then, they could adapt their behavior toward a person according to how another robot acts in their group. For instance, imagine that a robot in a kiosk at a hospital told another guide robot that a visitor was looking for their friend, who was recently in an accident. The information provided by the robot at the kiosk could then influence the guide robot to provide words of encouragement and support to the visitor as it guides the person to the friend's room in the hospital.

4.3 Structure III: Multiple Robots Shape an Interaction between Multiple Others

Structure III implies multiple robots shaping interactions through coordinated behavior (Figure 2(c)). For instance, Sadka et al. [98] showed that the motion of robotic bar-stools can encourage human–human interactions and increase positive encounters. Another example is the study by Connolly et al. [29] on group human–robot interactions involving robot abuse. In a team of 2 humans and 3 Cozmo robots, a confederate abused one of the robots after it made mistakes during the interaction. The other two robots either ignored the abuse events or reacted in response to it by expressing sadness toward the abused robot. Interestingly, the latter reaction led to participants being more likely to prosocially intervene to help the abused robot and stop the mistreatment by the confederate in comparison to former one. This was a surprising group social influence effect by robots, because people have many reasons to avoid conflict with a person that abuses a robot in a laboratory study [124]. In the future, we foresee more examples and scenarios with Structure III present demonstrating powerful group social effects in ISR, including conformity [99].

Structure III also brings new perspectives to swarm robotics. While most work in swarm robotics within HRI concerns operator control methods [70], swarm robotics in ISR is more about multiple robots shaping the interaction between other agents. An example is MOSAIX [4], a social swarm system designed to help humans in social tasks like opinion-mixing and brainstorming. The movement and mixing of the swarm appeared to engage people in a public exhibition and led to conversations about climate change. In the future, more work could be done to understand ISR with multiple robots and more human interactants than typically studied today.

5 CHALLENGES AND OPPORTUNITIES

This section discusses current challenges and also opportunities regarding ethical considerations, methodological approaches, and computational advances unique to Interaction-Shaping Robotics.

5.1 Ethical Considerations

In this section, we highlight the opportunities but also ethical risks and challenges of research and development in the field of ISR.

5.1.1 A Robot's Influence on Human–Human Connections. Positive relationships between people bring them feelings of happiness, security, self-esteem, and pleasure [49, 94]. Furthermore, close and positive relationships between people are essential to living a fulfilled and healthy life [134, 142]. On the contrary, when relationships between people are negative or nonexistent, people suffer from social rejection, loneliness, and poorer physical health [57, 116].

IEEE's guidelines on Ethically Aligned Design indicate that autonomous and intelligent systems should support human potential and ensure connections and relationships between humans [83]. Interaction-shaping robots have a unique opportunity to follow this suggestion by enhancing and promoting human–human connections. For example, robots have already been shown to increase human–human interactions and connections between child and caregiver [22, 47] and in care facilities for older adults [84, 97, 127]. Also, they can potentially detect if a person is isolated and encourage connections between them and others. This approach for alleviating human isolation by having robots promote human–human interaction is distinct from other methods in HRI to alleviate loneliness through human–robot interactions alone. While several robots have shown promise in reducing a person's loneliness and raising their mood [141], some have expressed concern that giving a person a robot to reduce their loneliness could isolate the person even further [38]. Regardless of the benefits or drawbacks of using robots to alleviate peoples' loneliness, using robots to encourage human–human interaction is a promising avenue that could increase human well-being and avoid potential risks of further isolation.

While reducing the risk of isolation and improving well-being, the risk of dependency on the robot cannot be fully eliminated. Instead of an individual being dependent on the robot, the functioning of an interaction between people could become dependent on the robot's interaction-shaping efforts. Therefore, we believe that it is valuable for an interaction-shaping robot to sustainably improve interactions and relationships so that the robot eventually becomes obsolete. This way, people can reap the benefits of human–human connections without being fully dependent on a robot to sustain them. Future research should investigate more the long-lasting effects of interaction-shaping robots beyond the interaction with the robot, as discussed in Section 3.5.

5.1.2 People's Unawareness of the Influence of Interaction-shaping Robots. Interaction-shaping robots face the ethical risk of deception when people are unaware of the robot's shaping attempts and its effects. Interaction-shaping can positively shape human–human interactions, for example, so that every group member's opinion gets heard [42], or so that people feel more comfortable when discussing difficult problems [14]. However, people are fully aware that a robot is influencing their interactions only in some contexts, while they may not be aware of its influence in others.

A person's possible awareness of the robot's influence might best be described as a spectrum between being fully aware and unaware. The literature has explored scenarios in which the human group members could be fully aware of the robot's influence on their interaction. People could become aware of the robot's influence through the context of interaction, e.g, a robot acting as a couple's counselor [132], or through the behaviors the robot demonstrates during interactions, e.g., when a robot intervenes in a conflict, it can openly address the conflict and suggests conflict resolution strategies [108].

When the robot uses non-verbal communication or shapes the interaction implicitly, it is more likely that human group members are unaware of the robot's influence. A robot acting as a group member or a peripheral facilitator might further increase unawareness of its influence. For example, participants sometimes noticed gaze cues used to encourage more participation from a less talkative person [42] as irregular patterns in the robot's gaze. However, they were unaware that the robot's gaze influenced their behavior relative to other humans in the game [43]. Additionally, people might have been aware of the robot's expressions of vulnerability [120], but they were not aware that their own behavior was shaped by the robot as a result of these vulnerable expressions.

Especially since people may be unaware that their interactions may be shaped by robots, it is important to consider the potential ethical risk of deception in ISR. Deception has been identified as an ethical risk for social robots in general [83, 146] and extends to interaction-shaping robots as humans might not expect their interactions to be shaped by a robot. IEEE's ethics guidelines suggest that "in general, deception may be acceptable in an affective agent when it is used for the benefit of the person being deceived, not for the agent itself"[83, p. 175]. In other words, deception in ISR might be acceptable in cases where there is consensus that the robot's influence benefits people (e.g., robots that express vulnerability [120] to help people feel more comfortable self-disclosing, robots that use gaze to elicit verbal participation from more quiet group members [44]). Nonetheless, research at the intersection of RoboEthics [139] and ISR is important to critically discuss the effects of interaction-shaping robots and establish recommendations for their development. These discussions will further help to prepare the public and policymakers for handling end-user robotic products capable of shaping interactions. Last, we suggest that future work explores interesting directions that might arise when thriving to reduce ethical risks. For example, in cases where it might be natural to hide a robot's intent, how would being upfront about the robot's goal to shape other agents' interactions affect how people perceive the robot and its social influence capacity?

5.1.3 Potential Bias in ISR. Interaction-shaping robots might inherit societal biases. The risk for bias is present in all of HRI, but it is of particular importance in ISR where the bias can affect other agents' interaction negatively. For example, Hitron et al. [53] showed that a robot giving turns in a debate according to gender biases reinforced gender stereotypes. However, reversing the robot's behavior dispelled these stereotypes [54]. Further, Rosenthal-von der Pütten and Abrams [96] and Winfield et al. [146] discuss the risk that machine learning algorithms known for developing biases [58] might transfer those biases when used to create robot behaviors, e.g., in resource allocation problems [62]. These biases might stem from societal biases captured in the data or occur due to nonrepresentative datasets [87]. To mitigate potential biases, future work in ISR needs to carefully consider sources of the data used to design or learn interaction-shaping robot behaviors.

5.2 Research Methods

Because multi-party HRI research has explored a large variety of contexts and robot applications, there are not many standardized methods, tasks, and approaches that allow for comparison across studies [81]. Additionally, theoretical models and frameworks for studying group interactions are needed to guide our understanding of how robots can shape interactions between other agents. Abrams and von der Pütten [1] proposed the I-C-E framework for studying groups by presenting definitions for inclusion, cohesion, entitativity, and methods that allow for measuring the different concepts. Despite these contributions, the authors highlight that these methods for understanding groups and their dynamics are scarce and are insufficient to understand the complex interactions in groups. Conversation Analysis, which is concerned with the fine-granular qualitative analysis of human–human interactions might offer one possible direction to understand interaction-shaping effects [88, 131]. Future work should invest in exploring new techniques to study interaction-shaping robots.

5.3 Computational Advances

We need computational advancements for developing interaction-shaping robots that can autonomously adapt to different group interactions and support their distinct needs [46]. Current work in HRI often uses sets of simple heuristics and interaction scripts to guide autonomous robot behavior in multi-party interactions. While these heuristics can provide a first approximation to appropriate behavior when driven by human psychology (e.g., References [42, 69, 126]), there is no guarantee that these hand-crafted policies capture all the essential information in the interaction that the robot may need to select optimal actions nor account for unexpected human behavior. To develop more robust interaction-shaping robot behavior, advances are needed in modeling relationships and group phenomena, state representations, and robot behavior control.

5.3.1 Modeling Relationships and Group Phenomena. ISR is concerned with shaping interactions that eventually result in shaping relationships among other agents. This can be achieved by leveraging group phenomena (e.g., group social influence [29]) or can in turn induce group social phenomena (e.g., cohesion [112]). This makes the perception of both relationships and group social factors in HRI essential to interaction-shaping robots. A path forward to improve robot perception in this regard is to bridge Social Signal Processing (SSP) [140] and ISR. Social Signal Processing has contributed many methods for computationally modeling social aspects important for human–human interactions. For example, prior work explored identifying dominant individuals [6, 9] or emerging leadership [12, 100]. In terms of group-level phenomena, there is also work on the recognition of social roles [3, 150], social relations [2], and cohesion [60]. In the future, it is important to extend these lines of research to more clearly understand causal relationships between group members' behavior, and how shifting perspectives (top-down camera view often used is SSP versus a robot's first-person view) may influence reasoning about group behavior.

5.3.2 State Representation: Recent work in multi-party Human–Robot Interaction has begun to advocate for representing social interactions with graph abstractions [72, 122, 137, 143], which would also benefit ISR as suggested by Figure 1. In these graphs, nodes often encode information about interactants and edges encode information about relationships. These graph abstractions could be used for a state representations in ISR, because they encode relevant data in a well-organized manner, which in turn could lead to algorithms that exploit the structure [48, 145] for better modeling of interactions and group constructs.

5.3.3 Robot Behavior Control. Finally, it is important to close the loop between perception and control in ISR. Advances from Reinforcement Learning and Imitation Learning might be suitable to map perceived group states with effective robot behaviors for shaping interactions among other agents. Early explorations of learning robot policies for ISR compare reinforcement learning and imitation learning approaches in the context of balancing human participation in conversations [43]. A challenge when learning robot shaping behavior is ensuring that the resulting policy is safe and appropriate for the given interaction context, e.g., learned gaze behaviors may be irritating, requiring careful hyper-parameter search and final model selection [43]. If future interaction-shaping robots can learn complex behaviors, then we might be able to discover shaping behaviors that are potentially unique to robots, not something that humans would naturally do or even be capable of doing.

6 CONCLUSION

This article defines ISR as robots that shape interactions among two (or more) other agents. Key factors of ISR characterize interaction-shaping robots according to their role in the interaction, the robot-shaping outcome, the form of robot influence, the type of robot communication, and the timeline of the robot's influence. Further, we highlight three unique ISR group structures where one robot shapes either a human–human or a human–robot interaction, or multiple robots shape the interaction among multiple other humans. These structures, in combination with the discussion on key factors, offer interesting avenues to explore a larger variety of interaction-shaping robots. It is essential that future work further advances our ethical understanding of ISR, robot autonomy, and methodological practices, but most importantly we hope that future interaction-shaping robots can support humans in flourishing by shaping their human–robot and human–human interactions.

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