Robots in Groups and Teams: A Literature Review

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Autonomous robots are increasingly placed in contexts that require them to interact with groups of people rather than just a single individual. Interactions with groups of people introduce nuanced challenges for robots, since robots' actions influence both individual group members and complex group dynamics. We review the unique roles robots can play in groups, finding that small changes in their nonverbal behavior and personality impacts group behavior and, by extension, influences ongoing interpersonal interactions.

CCS Concepts: • **General and reference → Surveys and overviews**; • **Human-centered computing →** *User studies*; Interaction design theory, concepts and paradigms; • **Computer systems organization →** *Robotics*.

Additional Key Words and Phrases: human-robot interaction, groups and teams

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1 INTRODUCTION

Catalyzed by the adoption of robots in manufacturing during the 1970s and 80s, questions quickly followed regarding how robots might impact group practices, productivity, and even social dynamics. Despite the rapid increase of robots in the workplace and a couple of early examinations [8, 9], suggesting both advantages (reduced fatigue) and disadvantages for workers (increased human downtime, reduced face-to-face time with coworkers), research exploring a robot's impact on people largely focused on dyadic interactions (i.e. one robot interaction with one human [54, 58, 65, 98, 147, 172]). It was not until decades later that research in human-robot interaction began expanding from a primarily one-to-one, level to consider a robot's influence at the group level (e.g., groups, teams, workplaces, organizations, families, classrooms [67]). Despite the recent growth in research investigating the influence of robots within groups of people (see Figure 1 for some descriptive examples), our overall understanding of what happens when robots are placed within groups or teams of people is highly limited. Developing such understanding is essential for the field of computer-supported collaborative work (CSCW) since almost all work involves groups or teams to some degree [93], the performance of which is highly dependent on group dynamics

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Fig. 1. Descriptive examples of robots interacting with human groups: (a) a Furhat robot completing a sorting task with two people in a museum [161], (b) two EMYS robots and two people playing a card game in a lab setting [31], (c) a Robovie robot guiding people in a shopping mall [154], and (d) a Nao robot playing a collaborative game with three people in a lab setting [164].

(e.g., [64, 80, 192]). Without a detailed understanding about how robots influence the dynamics, development, and outcomes of groups, efforts to develop robots that effectively support groups and teams are likely to plateau.

When we use the term groups, we refer to “two or more individuals who are connected by and within social relationships” [47]. We explicitly include dyads (two people) when we refer to groups [191], but acknowledge that there is disagreement about that categorization (e.g., [123]). We use the terms team, work-group, and task-group interchangeably to refer to those groups that 1) share one or more common goal(s), 2) are interdependent in their tasks, and 3) interact socially [27, 93]. It is also important to note that when we refer to groups and teams in the context of this paper, we refer to groups and teams of *people* and do not necessarily assume the robot to be a constituent member of the group. Our interest is primarily in understanding the impact robots have on groups and teams of people.

Groups exhibit unique emergent properties that cannot be fully understood by merely aggregating the behavior and characteristics of individuals [47, 106, 159, 192]. For example, research has shown that the collective intelligence of groups is independent of the intelligence of the individuals that constitute the group and instead dependent on a group’s emergent social processes [192]. Some of these emergent social processes include interpersonal dynamics, organizational level factors, and group processes for successful interaction (e.g., conflict management, establishment of group norms, maintaince of shared mental models, development of transactive memory systems) [19, 27, 105, 190, 194, 195]. Groups also exert influence over group members as they shape decision making [10, 151] and form social identities [170]. Transitioning from dyadic interactions (one robot one person) to interactions with groups (one or multiple robots with two or more people) constitutes a fundamental change in complexity that is neither captured by current theory in human-robot interaction [60, 79], nor do existing technical approaches for human-robot interaction readily scale to groups [25, 115, 116].

While research on computer-supported cooperative work (CSCW) originated out of an interest in groups and teams [63] and offers a rich body of work examining the impact of technology on groups and teams, CSCW theory does not readily capture how groups and teams are influenced by robots. Research on CSCW has consistently highlighted time (e.g., synchronous vs asynchronous) and place (e.g., face-to-face vs. electronic) as dimensions that are among the most relevant when theorizing a technology's impact [61, 75, 96], even as CSCW has moved to what Wallace and colleagues [187] call the "Post-PC Era" and has broadened its scope to include technologies other than PCs. Existing frameworks and theories work well when technology is theorized predominantly as a tool or infrastructure to support teamwork [187], however, do not well extend to autonomous robots that can take on roles within groups as teammates or constituent members [137]. People have demonstrated a unique response to robots [34], as opposed to other non-physically embodied agents, demonstrating increased compliance [12, 40], learning gains [107], and preference scores [186] in human-robot interactions. The physical presence of robots and their ability to be perceived as independent agents differentiate them from other technologies (e.g., virtual agents, mobile phones, videoconferencing software), and thus require specific investigation as to their distinct influence on groups and teams of people.

For these reasons, we believe it is both timely and necessary to provide a review of studies focusing on robots interacting with groups of people to provide both an objective insight into where the field stands to date and further push researchers toward areas of potential need and interest. Our review seeks to answer three primary research questions: How does a robot's behavior shape group dynamics and people's behavior within the group? What are appropriate roles for robots to adopt in a variety of settings? And how does a robot's behavior affect how people in the group behave towards one another?

1.1 Differences between Robots Interacting with Groups and with Individuals

As researchers began exploring robot interactions with multiple people, it has become clear that several aspects of the interaction change when a robot engages with multiple people as opposed to a single person. Notably, groups of people 1) are more likely to interact with robots, 2) exhibit intergroup bias in their interactions with robots, 3) pay less attention to robots, and 4) distinctly externalize their mental states. In this section, we describe work that has exposed these distinct aspects of human-robot group interactions and explore possible explanations for these observed differences between how groups and individuals interact with robots.

When given the choice of whether or not to interact with a robot in their environment, groups of people are more likely than individuals to engage with the robot. Groups, as opposed to individuals, were significantly more likely to interact with a robot receptionist, that was positioned near an entrance to an academic building [56, 120]. Additionally, unsuspecting university students were three times more likely to allow a robot to both enter and exit their restricted access dormitory building if they were in a group rather than if they were by themselves [18]. From these research studies, it seems that people feel more comfortable engaging socially with robots from the safety of a group as opposed to being alone.

Groups of people have also exhibited more competitive and aggressive behavior toward robots than toward individuals. A likely explanation for this behavior is the introduction of intergroup bias in groups composed of multiple people and one or more robots, where humans consider themselves as an ingroup and the robot(s) as an outgroup. Members of groups with intergroup bias adopt an "us versus them" mentality, characterized by favoring ingroup members and opposing outgroup members [14, 169]. Intergroup bias applied to robots has demonstrated similar effects, where a robot ingroup member is perceived as more anthropomorphic and is evaluated more positively than a robot outgroup member [71, 94]. Several HRI research studies support the idea that humans within a human-robot group naturally adopt intergroup bias where they treat robots as outgroup members. For example, in a research study where pairs rather than individuals played a game against a robot, the pairs exhibited more competitive and less cooperative behavior towards the robot [24]. Similarly, groups of three humans exhibited more greed and competitive behaviors toward robots than individuals [52]. Outside the context of competitive games, children and young adults have shown a tendency to exhibit bullying behaviors toward robots in public spaces [17, 20, 143]. These research studies strongly suggest that robot members of human-robot groups are often regarded as having a distinct membership in the group, often resulting in the antagonistic treatment of robots.

Another difference between robot interactions with individuals and groups of people is the presence of human-to-human interactions. Groups of people, as opposed to individuals, who interacted with a robot receptionist spent more time engaging with the robot, however spent less time interacting directly with the robot [56, 120]. The decreased focus on the robot due to the presence of other humans in the group has also been shown to have adverse effects on the learning outcomes of children. After listening to two robots playing out interactive narratives, learning and recall scores for children in groups of three were shown to be worse than those of individual children [100, 101]. A likely explanation for this result is that the children directed less attention to the robots when they were in groups of three because they were also attending to one another, and thus did not retain as much of the information the robots were trying to convey.

Additionally, the way that people express their internal states (e.g., emotions, attitudes) seems markedly different when comparing a one-on-one human-robot interaction with a human-robot group interaction involving multiple people. For example, the accuracy of machine learning classifiers designed to recognize disengagement in children significantly decreased in group contexts when the classifiers were trained on data with individuals [102]. However, classifiers trained on videos of children within groups of three predicted engagement more accurately [102]. These findings illustrate the differences in how children express disengagement when interacting alone with robots as opposed to interacting alongside two peers with the same robots, as well as the need for robots to develop the capabilities to sense human internal states distinctly in one-on-one and group contexts.

In sum, this literature provides compelling evidence that people interact differently with robots when they are alone than when they are with other people. This review seeks to highlight the research unique to robots interacting with groups of people: the nonverbal and verbal behaviors a robot can use, contexts in which human-robot group interaction has been explored, and the influence of robot behavior on how people in the group interact with one another.

This review is organized as follows. In Section 2 we detail our selection method for the papers that we included in this review. We then present the central themes and findings resulting from our analysis of these papers in Section 3: descriptive characteristics of the robots and groups (Section 3.1), robot behavior studied in groups (Section 3.2), group interaction contexts (Section 3.3), and robots' influence on human-to-human interactions (Section 3.4). We summarize these findings in a framework that we describe in Section 3.5. In Section 4, we discuss this body of work focused on robots interacting with human groups and teams with a specific focus on implications for theory, design, and research methods.

2 REVIEW METHOD AND CORPUS

We conducted a systematic review of the experiment designs, methodologies, and analytic techniques that form the foundation of research studies investigating robots interacting with groups and teams. Our review takes stock of existing work and highlights areas of opportunity for future research. We included studies that satisfied the following criteria:

(1) The study must include at least one physically embodied robot.
(2) At least two locally present people must interact with the robot(s) simultaneously.
(3) The robot(s) must be autonomous or perceived to be autonomous interactant(s).
(4) The study must explore group-level phenomena and provide a direct contribution to our understanding of how robots interact with and influence groups of people.

These criteria were chosen to focus this review on studies that investigate how physically present autonomous robots shape interactions with multiple people simultaneously. We exclude studies that focus on one person interacting with multiple robots [50, 51] because our focus in this review is on how robots can influence groups of *people* and we do not assume that robots are constituent members of the groups studied. We do not include studies pertaining to mobile robotic presence systems, or telepresence robots [131, 132, 162, 171], because they are dependent upon a human in the loop and lack the autonomy necessary to be considered agentic robots. Similarly, this excludes numerous studies conducted using remote-controlled robotics such as rovers [165, 182], rescue robots and drones [125], and surgical robots [15, 28, 36, 135], since these robots fulfill more the role of robotic tools rather than autonomous agents. Excluded as well are technical papers wherein the primary focus is on systems designed for multiple-human interaction, however, do not demonstrate the influence of the robot's actions on the group. For example, this applies to papers focused on analyzing multi-person groups for approach strategies [5, 38, 175], localizing and parsing relevant group member speech, and analyzing group cues for topic shift and engagement [115].

Using the inclusion criteria described above, we conducted an exhaustive search of papers within top-tier HRI outlets including the ACM/IEEE International Conference on Human-Robot Interaction (HRI), the IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), the International Journal of Social Robotics (IJSR), and ACM Transactions on Human-Robotic Interaction (THRI). Additionally, we conducted a Google Scholar search using the terms "robots in groups" and "robots in teams" as well as for the publications of all authors who participated in the Robots in Groups Workshop event hosted at the 2017 ACM Conference on Computer-Supported Cooperative Work and Social Computing (CSCW). We conducted further Google Scholar searches of all authors attached to our existing literature collection as well as relevant author citations within these sources. We set a cut-off date of publication for inclusion in this review at April, 2019. The search for publications to include in the review was conducted by the first and second authors and was modeled after the literature search described in a recent review on robots for education [16]. The first and second authors agreed together upon which papers satisfied the inclusion criteria. The method we used to search for and include papers in the review is summarized in Figure 2[1].

In total, we collected a corpus of 103 peer-reviewed scholarly papers for our review, which contain 101 distinct studies – human-subjects experiments with a defined experimental design. There is a difference in the number of papers and research studies because some papers include multiple studies and some papers refer to the same study.

In order to quantify the differentiating characteristics of this body of work, we categorized features related to the robot, the human-robot group as a whole, and the experiment setup in each of the studies included in this review. To capture differences in robots' appearance and behavior, for each study we annotated the type of robot(s) used, whether or not the robot(s) have a head and eyes, the robot control methodology (Wizard-of-Oz or autonomous), the role of the robot (leader, peer, or follower), and the main robot behavior(s) examined (locomotion, gaze, gestures, content

[1]The number of papers from the RO-MAN conference is approximate due to the lack of online access to the proceedings from 1998 and the lack of distinction between short and full papers in some of the proceedings.

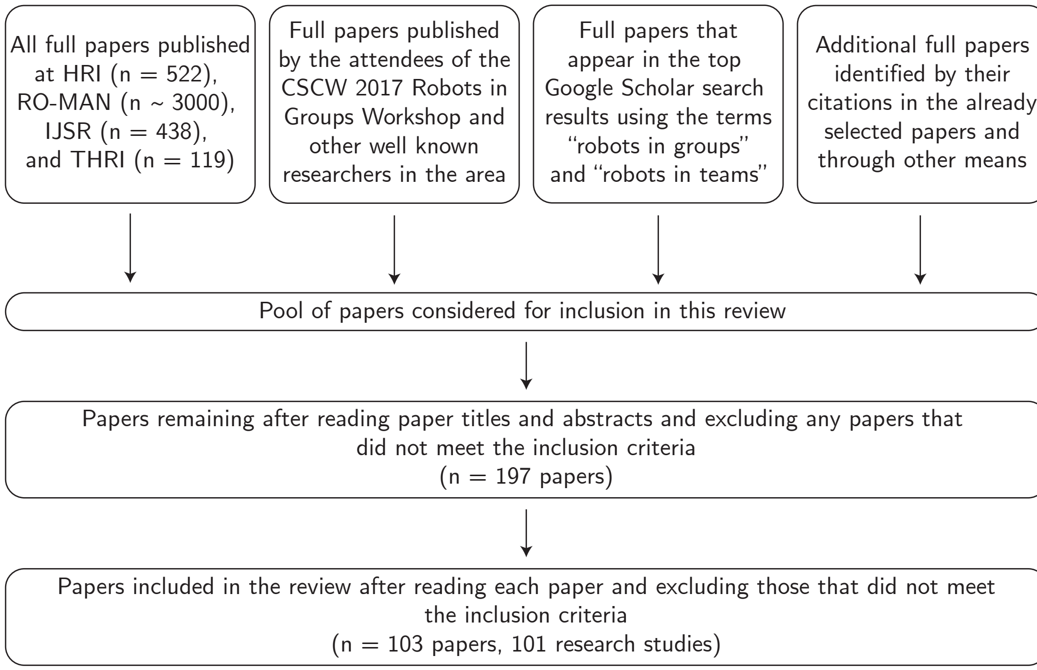

Fig. 2. In this diagram, we illustrate the method we used to select the research papers that are included in this review.

delivery, personality, and/or emotion). In order to analyze characteristics of the group as a whole, for each study we denoted the composition of the group (the number of people and the number of robots) as well as the type of the group according to [109] (loose association, task group, or intimacy group). To evaluate the variety of experimental setups, for each study we captured the country where the study was conducted, the setting of the study, the study design type (experimental or observation-based), the number of between subjects conditions, the number of groups, the number of total participants, and the number of study sessions. The research studies included in this review as well as their categorized features are listed in Table 1 in Appendix A).

A majority of research studies have come from the United States, Japan, and Europe, see Figure 3(a). Most of the studies had an experimental study design (82% of the studies). For each between-subjects condition in these experimental studies, the number of groups in each condition ranges from 1 to 373 with a median of 12 groups as shown in Figure 3(b). A majority (79%) of the experimental studies in this review relied on only one interaction session, Figure 3(c). Exceptions include a study in which a QRIO robot was integrated into a preschool classroom and interacted with preschoolers during *45 distinct sessions* for on average 50 minutes per session over the course of 5 months [174].

3 FINDINGS

After carefully selecting the studies to include in this review, we next focus on the most significant contributions of this body of work. We highlight the main descriptive characteristics of the robots and groups, the robot behaviors studied within groups, the interaction contexts of these studies, and results demonstrating robot influence on human-to-human interactions within groups. We summarize these findings in a framework depicting how robots influence the behavior of human-robot groups (Figure 7).

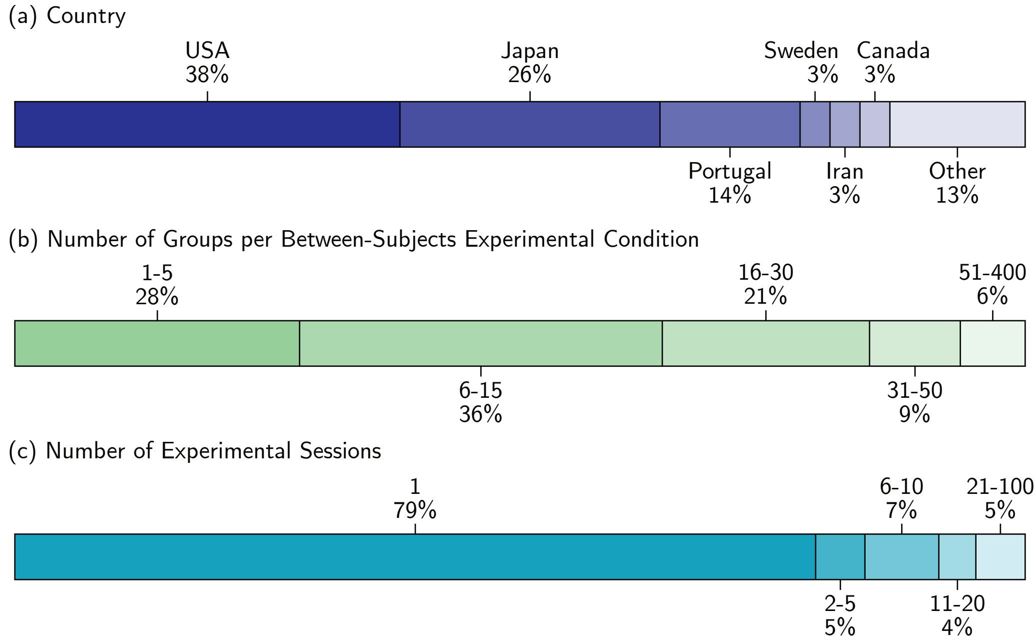

Fig. 3. In the studies we review, we highlight the (a) countries where the studies were run, (b) the number of groups per between-subjects condition in the experimental studies, and (c) the number of interaction sessions in the experimental studies.

3.1 Descriptive Characteristics of the Robots and Groups

The descriptive characteristics of robots and the groups with which they interact have a considerable influence on the types of interactions that can occur and their outcomes. From the studies included in this review, we focus on the group compositions, the types of robots used in the studies, and the control methods used for the robots.

Of the studies in our corpus, a majority have examined groups consisting of a variable number of people and one robot (e.g., a robot approaching and interacting with groups of varying sizes in a shopping mall), two people and one robot, and three people and one robot, see Figure 4(a). Few studies have explored groups consisting of more than one robot interacting with a group of people or robots interacting with a defined group of more than 3 people. Future work is needed to study the effects of more robots and more people within groups. For example, it is likely that as the number of people within a group increases, the robot's effect on the individuals within the group will weaken. This has been demonstrated on a smaller scale in Leite's work where children's learning and recall scores decreased when groups of three children, as opposed to a single child, received educational instruction from two robots [100, 101].

A variety of robots have been studied interacting with groups of people: highly anthropomorphized or human-like robots (i.e., android robots, e.g., Android Repliee Q2), robots with a body shape that resembles that of a human (i.e., humanoid robots, e.g., Robovie, Nao), robots that resemble animals (e.g., PARO), simple robots that can exhibit social behavior (e.g., Keepon), robots that have a face and no body (e.g., EMYS), and robots that do not have a social appearance (e.g., Turtlebot, Roomba). For a comprehensive review of socially interactive robots and their defining

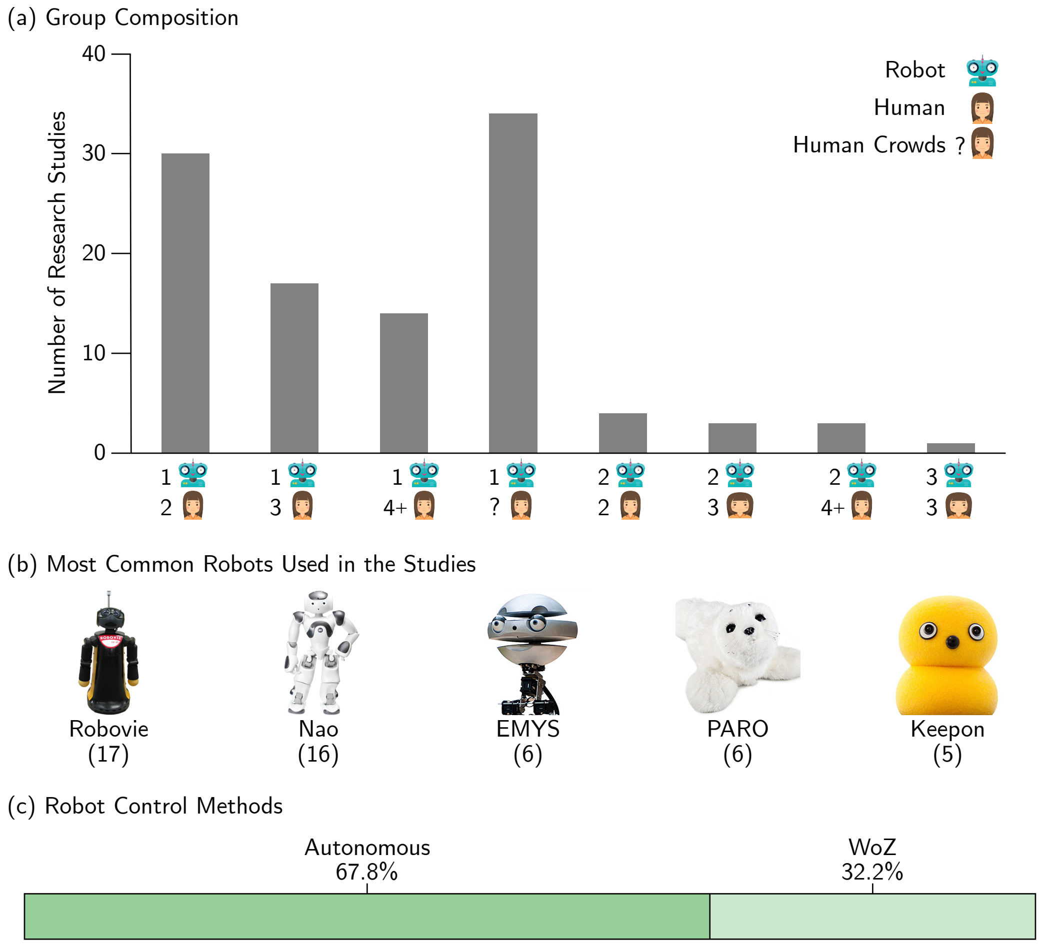

Fig. 4. We display the (a) composition of human-robot groups studied in the literature as well as (b) the most commonly used robots in these studies and the (c) control methods for these robots.

characteristics, please refer to [44]. Figure 4(b) displays the most commonly used robots in the studies included in this review.

The appearance and capabilities of a robot greatly shape what the robot can physically do and how the robot can communicate with the people in the group. Robots with more human-like features (e.g., a face and eyes, the ability to physically move around, speech-to-text capabilities) can communicate using a wider array of social signals that people can easily discern (e.g., gaze, proxemics, gestures, human language). In fact, 83% of the studies in this review study a robot that has a head and eyes. The inclusion of both a head and eyes in the majority of robots used in studies with groups may speak to the importance of a robot's ability to direct attention in a group and leverage accessible and familiar social cues, establishing it as a social agent in the context of a human-robot group. However, this could also be influenced by which robot platforms are available for purchase (most have a face and eyes), so the importance of these features should be considered keeping this in mind.

Robots in these studies have either been controlled autonomously or by the Wizard of Oz (WoZ) method. The majority of studies have used fully autonomous robots (67.8%) requiring no human input to control, as shown in Figure 4(c). Autonomous robot control more closely simulates how robots will interact with people in non-research contexts and has a low burden on researchers while conducting studies. Other studies have used the WoZ method (32.2%) to simulate autonomy by involving a human 'wizard' who controls aspects of the robot's behavior (e.g., speech recognition and generation). While the WoZ method does not resemble how most robots will be controlled within non-research contexts in the future and WoZ requires a high burden on the 'wizard' during the study, the WoZ method does enable the robot to have a wider range of more sophisticated actions in its interactions with people. Although the two control methods have different strengths, they have both been used to make significant contributions to the study of robots interacting with human groups and teams.

3.2 Robot Behavior in Groups

Just like people, robots can influence group interactions through their nonverbal and verbal behaviors. A robot's use of nonverbal behaviors (e.g., gaze, proxemics, gestures) can socially cue group members to produce desired responses. Additionally, robots can express emotion and personality verbally, which can shape the overall group dynamic.

3.2.1 Nonverbal Behavior: Gaze, Proxemics, and Gestures. A sizable portion of research on robots in groups focuses on ways in which a robot can shape the interaction dynamics between people using nonverbal cues and interventions. Collectively this work demonstrates a powerful influence that robots can exert on groups using gaze, proxemics, and gestures.

Speaking specifically to robot gaze in groups, studies have found that groups of varying sizes can easily recognize a robot's gaze [72] and interpret a robot's prioritized target from a robot's gaze cues [89]. Robots can also use gaze in tandem with other cues, such as smiles and speech pauses, to influence turn-taking between human group members and signal upcoming conversational turns for the robot [160, 161]. Beyond the ability to influence turn-taking, robots have also been shown to shape people's conversational roles using gaze in a group [128].

Proxemics, or the way in which a robot is physically positioned in groups, has also been shown to influence human-robot group interactions. People in crowded spaces prefer robots that maintain a comfortable distance [86]. People also prefer robots that approach their group when the robot is in the line of sight of group members and when the robot aims to occupy a spatial opening in the group [13]. A robot's body orientation also influences its interactions with groups of people. In a shopping mall, bystander groups have been observed to be larger and more engaged when the robot walked backwards, facing the group, rather than alongside them [154]. Additionally, a robot that leverages its body position and gaze toward groups in a brainstorming task was found to facilitate feelings of inclusion and belonging to the group [179]. People also alter their own proxemic distance to robots based on their context and the robot's navigation strategy. For example, people move closer to a stationary robot if the group contained both a child and an adult [129], and people were observed to navigate with lower accelerations (indicating possible increased comfort) around robots navigating autonomously with state-of-the-art navigation algorithms as compared with teleoperated robots [118].

A robot's physical gestures can enhance its interactions with groups of people. People perceive a robot more positively if it considers the social appropriateness of its pointing gestures (e.g., it is not always socially appropriate to point at people [110]). Robots that produce gestures that are more organic and natural, allowing for interruptions in the production of gestures and featuring parameterization of gestures, have been shown to increase both the number of people who communicated with it and the length of the interaction [91]. Additionally, robots are more effective at conveying their arm motion intent when they can balance the legibility and predictability of handover motions when interacting with a group of people [39]. Non-anthropomorphic robots that do not use verbal language and only communicate through gesture and movement have been shown to influence people's gaze towards the robot, perceptions of the robot's sociality [68], as well as the evenness of the group's conversational backchanneling turns [176].

3.2.2 *Verbal Behavior: Personality and Emotion.* A robot's speech can powerfully influence both its perceived personality and emotion, which in turn shape the overall dynamic of the group and the behavior of its members.

Robot personality characteristics (e.g., collaborativeness, competitiveness, trustworthiness, and warmth) are often communicated verbally, with profound effects on the group. In a series of studies employing two robots playing a partnered card game with two people, researchers examined how competitive versus relationship oriented personalities impacted group impressions [29–32, 133]. Competitive opponent robots and relationship-driven partner robots received the most gaze attention [133], but overall, people tended to prefer a relationship-driven robot as a group member [32], at least in the game context. People's preferences for robot teammates also shifted over time, such that people tend to prefer robot teammates with personalities (collaborative or competitive) that reflect their own [31, 32]. Time in general seems to be a critical factor in many instances as trust in human-robot teams forms over time [29, 30] and perceptions of and relationships with robots tend to evolve over time as well [111].

Robots can also express emotion verbally, shaping how people within a group behave and perceive the group. Robots have been shown to influence groups of people by displaying emotional cues [31], recognizing human emotions and empathizing with members [103, 136], and shaping the affective status, or mood, of a group and its membership [3, 66, 178, 185]. However, it is not simply a matter of saying that emotion displays make better robots, as the type of robot-enacted emotion display matters. For example, robots that expressed group-based emotion expressions were perceived as more likable and trustworthy than robots that expressed individual-based emotion expressions in human-robot groups playing a game of cards [31]. This research as a whole suggests great promise in using robots to facilitate positive group emotion, but there remain many gaps for researchers to explore in understanding precisely when and in what contexts the range of emotional expression may be influential or effective.

3.3 Interaction Context

In order to gain a broader understanding of the studies that have been conducted examining robot interactions with groups of people, it is necessary to examine the context of these interactions. We specifically focus on the study settings, the roles robots adopt within the group, and the type of the group, highlighting how these contextual factors have shaped this area of research.

3.3.1 *Robot Roles and Interaction Settings.* To gain better understanding of the roles robots take on as members of human-robot groups, we examined the settings in which group interactions occurred and the roles that the robots performed within those settings. We distinguish between lab settings (environments controlled by and chosen by researchers) and field settings (natural settings where participants would be found even when the experiment was not taking place). For field studies, we further categorized each study according to a specific setting (e.g., museum, shopping mall).

Additionally, we distinguished between three roles the robot took on during studies: *follower*, *peer*, or *leader*. A robot in the role of a *follower* reacts to interaction initiatives from people, follows

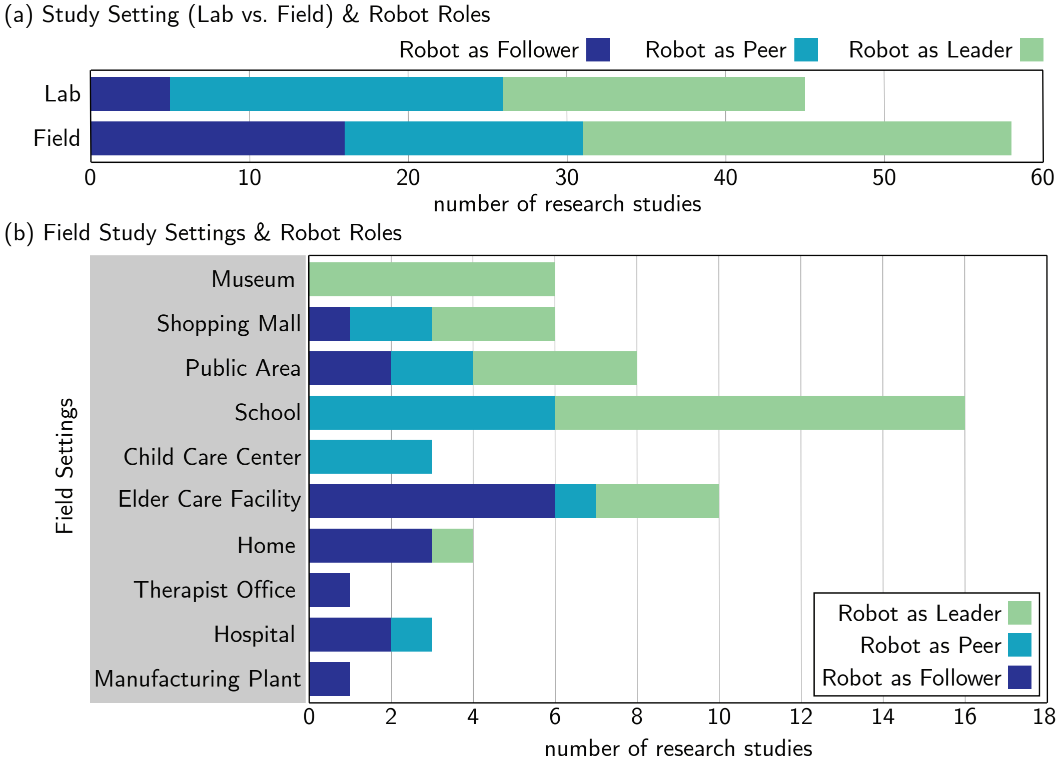

Fig. 5. We visualize (a) the number of studies conducted in the lab and in the field and the robot roles found within each setting and (b) the number of studies conducted in specific field setting and the robot roles found within each field setting.

instructions, or performs a service task to help people (e.g., a hospital materials delivery robot). A robot in the role of a *peer* is positioned similarly to a human in initiating and driving interactions (e.g., a robot collaborating as a partner on a shared task). A robot in the role of a *leader* initiates and guides interactions or facilitates the behavior of the people it interacts with (e.g., a robot tutor). Figure 5(a) visualizes the number of studies conducted in both the lab and the field with each of the three robot roles (follower, peer, and leader) and Figure 5(b) shows the number of studies that have been conducted in each specific field setting with each of the three robot roles. None of the studies were conducted in multiple settings, however some of the studies investigated multiple robot roles and the count for each of the roles was incremented by one.

It is important to observe that more than half (57.4%) of the studies have been conducted in the field, as shown in Figure 5(a). This stands in contrast to the human-robot interaction literature in general where, for example, of the full papers containing human-subjects studies accepted to the 2018 ACM/IEEE International Conference on Human-Robot Interaction (HRI), only 16.7% of the studies were conducted in the field (66.7% were conducted in the lab and 16.7% were conducted online, e.g., Amazon Mechanical Turk). As a result of the high proportion of studies conducted in the field, this body of work has a strong grounding in and applicability to real-world environments as well as a proved robustness to the more chaotic and complex interactions that occur outside the lab.

In Figure 5(a), we can also see that nearly half of the studies conducted in lab settings have investigated robots in peer roles (46.7%), whereas in field settings the smallest percentage of studies have investigated the robot in a peer role (25.9%). Robots in the field are usually either programmed to convey the same information doing repetitive tasks in the role of a leader or are designed to be under the direct supervision of people in the role of a follower. The lack of peer robots studied in the field is likely due to the challenge of equipping a robot in unconstrained settings with all the necessary skills and knowledge needed to effectively interact with people as a peer. Many of these essential skills are not unique to robots interacting with groups, such as natural language understanding, intent prediction, and emotion expression detection. In addition to these skills, robots interacting with groups of people as a peer and in more flexible and complex roles also must construct models of the relationships between the people with whom they interact, choose which person or people to address, and predict how their actions influence multiple different people. As these underlying technological components that support robots interacting socially with groups of people improve, robots will be able to take on more sophisticated, flexible, and complex roles in the unstructured and unpredictable field settings.

Certain types of settings seem to suit particular robot roles better than others, see Figure 5(b). In settings where the desired behavior of the robot is repetitive and consistent, especially in conveying information, robots are often put in the role of a leader, for example, explaining museum exhibits [155, 160, 161, 193], giving directions to people in a shopping mall [140, 154], and tutoring children [4, 21, 41, 84]. In settings where robots are designed to provide companionship to people, robots are often given the role of a peer, such as playing with children in day care centers [174] and learning alongside children in educational settings [69, 117]. In complex settings where robot mistakes can be costly, robots are often positioned in the role of a follower, where their actions are either controlled or monitored and can be corrected by the people around them, for example, delivering items within a hospital [111, 126], working alongside people in a manufacturing plant [144], and vacuuming people's homes [45, 46, 166].

Additionally, by examining Figure 5(b) it is clear that some settings have received more attention than others. For instance, about twice as many studies have been conducted with children in school settings than with adults in the workplace (e.g., hospital, manufacturing plant, therapist office) and people in home environments combined. In particular, these two environments, adult workplaces and homes, are the places where people spend the majority of their time and where robots have already had great influence and impact (e.g., vacuum cleaning robots, voice assistant devices, manufacturing plant robots, mobile delivery robots). As research continues exploring robots interacting with groups of people, more studies examining robots in adult workplaces and home environments are necessary to better understand the influence of robots on people in these environments and advance the robotic technology necessary for robots to operate effectively in these important settings.

3.3.2 Group Types. Another important contextual factor to consider when examining this work on robots interacting with groups of people is the type of the group. We distinguished between three group types using those experimentally derived by Lickel et al. (2000) [109]: intimacy groups, task groups, and loose associations. *Intimacy groups* are characterized by close personal relationships (e.g., romantic partners, friends, families). *Task groups*, or teams, are generally oriented around a shared task or interest (e.g., an airline flight crew, a student campus committee). *Loose associations* include both temporary assemblies of people (e.g., people in line at a bank, people waiting at a bus stop) and longer-term shared interests or interactions (e.g., neighbors, people who enjoy classical music). Interactions within the different group types have different characteristics (e.g., entitativity, permeability, duration, size) and are governed by distinct social rules and norms [26, 109]. Figure

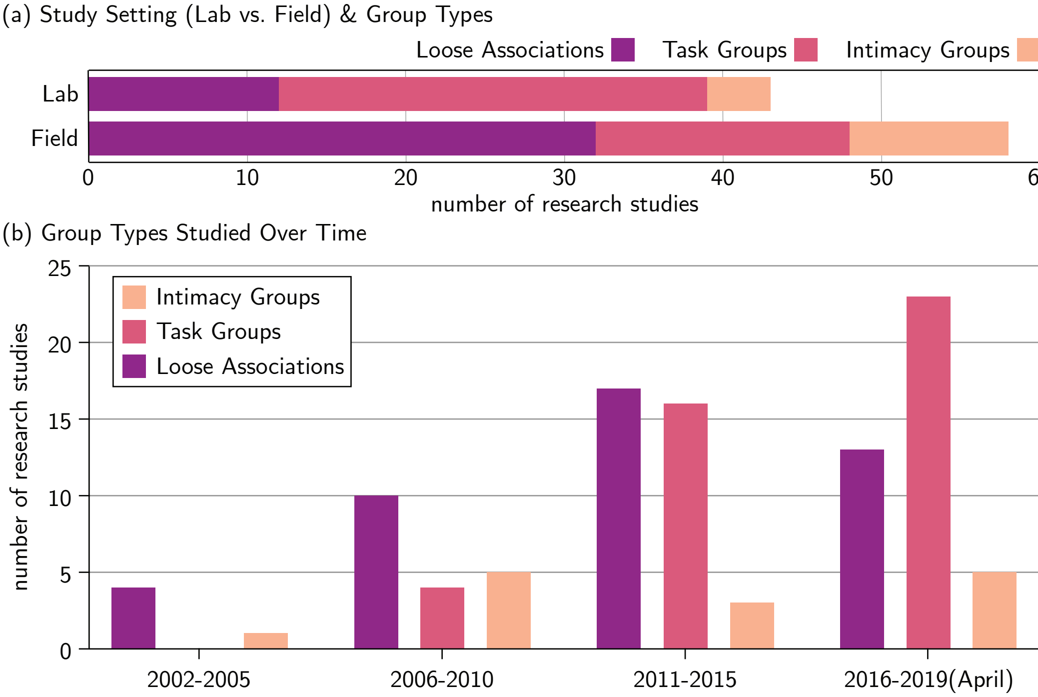

Fig. 6. We display (a) the number of studies conducted in the lab and in the field and group types in each setting and (b) the number of studies conducted over time for each group type.

6(a) displays the number of studies conducted in both the lab and the field, and within each study setting, the number of studies that examine each of the three group types. Figure 6(b) shows the number of studies that have explored each type of group over time.

In Figure 6(a), we observe that the most studied type of group are loose associations, especially those in field settings. These studies, for example, have analyzed the effectiveness of using robots to improve the mood and quality of life of elderly people [23, 66, 139, 184, 185], explored the use of nonverbal behaviors in robot exhibit explanations to enhance the experience of people attending a museum [91, 155], and examined methods to both effectively and safely navigate within a shopping mall [20, 86, 154]. This work studying robots interacting with loosely associated groups also dominated the early work (2002-2010) in this research area, see Figure 6(b).

Since 2010, studies examining robot interactions with task groups has risen dramatically, as displayed in Figure 6(b). In field settings, studies involving task groups have explored the utility of robots that deliver medical supplies in hospitals [111, 126], the incorporation of robots as social co-workers in manufacturing teams [144], and the effectiveness of robot teachers and tutors that facilitate learning interactions with multiple students [4, 22, 41, 84, 163]. Studies in the lab involving task groups have explored how robots can shape key aspects of human-robot teaming that are unique to the type of interactions that occur in task groups (e.g., conflict resolution [81], distribution of decision making authority [57], moderation of collaborative tasks [157], synchronization one's behavior with the group [73, 74]). As robot capabilities continue to improve and an increasing number of robots are developed to join teams of people, it is likely that work focused on robot teammates in task groups will continue to grow.

3.4 Robot Influence on Human-to-Human Interactions

Robots are not only able to shape how groups of people interact with it, there is also increasing evidence that robots can influence the relationships and interactions that people have with *the other people in the group*. Robots have been shown to shape human-to-human interactions in groups by increasing human social connection, mediating conflict, and shaping positive team dynamics.

Across a variety of settings, there is evidence that robots can encourage and increase social interactions among the people in a group with one another. Robots have demonstrated a positive influence on the amount of verbal communication and interaction among older adults within care facilities [139, 177]. Similarly, studies of robots moderating inter-generational groups [77, 158] have shown promise in engaging multiple generations in meaningful interaction. Also, robots that promote social skills development in children with ASD have shown to be effective in increasing social engagement between these children and others in their group, whether with their caregiver [145], another playmate [88], or with a therapist [196].

In moments of conflict between human members of a human-robot team, a robot's actions can influence how conflict is resolved. For example, robots have demonstrated success in directly mediating resource conflicts (e.g., fighting over the same toy) between children [149]. Another study showed that a robot intervening in a team's conflict after a team member made a hostile remark increased the salience of conflict and forced team members to actively engage with the conflict [81].

Robots have also demonstrated the ability to shape human-robot team dynamics, positively influencing how people interact with each other. For example, robots have been found to improve performance in a collaborative game between pairs of children by asking task-focused questions and perceptions of performance on the same task between pairs of children by asking relationship-oriented questions [163]. Another study that used a robot moderator during a three-person collaborative game showed that group cohesion could be actively influenced by the robot based on its behavior [157]. Tennent and colleagues [176] introduced a swiveling microphone robot ('Micbot') capable of facilitating more balanced participation during a three-person team's decision making discussion. Finally, a robot's verbal expressions of vulnerability have shown "ripple effects" in a group by increasing how likely human members of the group are vulnerable with one another [164]. These studies illustrate the influence robots have to shape group dynamics and the behavior of people in a group through direct intervention, peripheral non-verbal movement, and indirect verbal expression.

3.5 Summary of Findings

In order to synthesize the conclusions made from the studies discussed in this review, we present a framework that describes how a robot's actions influence the behavior of a human-robot group (Figure 7). Based on our findings we distinguish between three key factors that explain how robots can influence the behavior of human-robot groups: descriptive characteristics of the robot(s) and the group, robot behavior, and interaction context. As we discussed in Section 3.1, descriptive characteristics of the robot(s) and group (the group composition, the type of robot, and the robot control method) affect what a robot can and cannot do within a group as well as the magnitude of the robot's influence on the people within the group. In Section 3.2, we described how both nonverbal robot behavior (gaze, proxemics, and gestures) and verbal robot behavior (personality and emotion) can shape how people in the group perceive and interact with robots and the group as a whole. We explored how the interaction context affects the nature of the interactions that occur between groups of people and robots in Section 3.3, where we focused on the interaction settings (e.g., lab, home, school), the role of the robot (leader, peer, and follower), and the type of the group

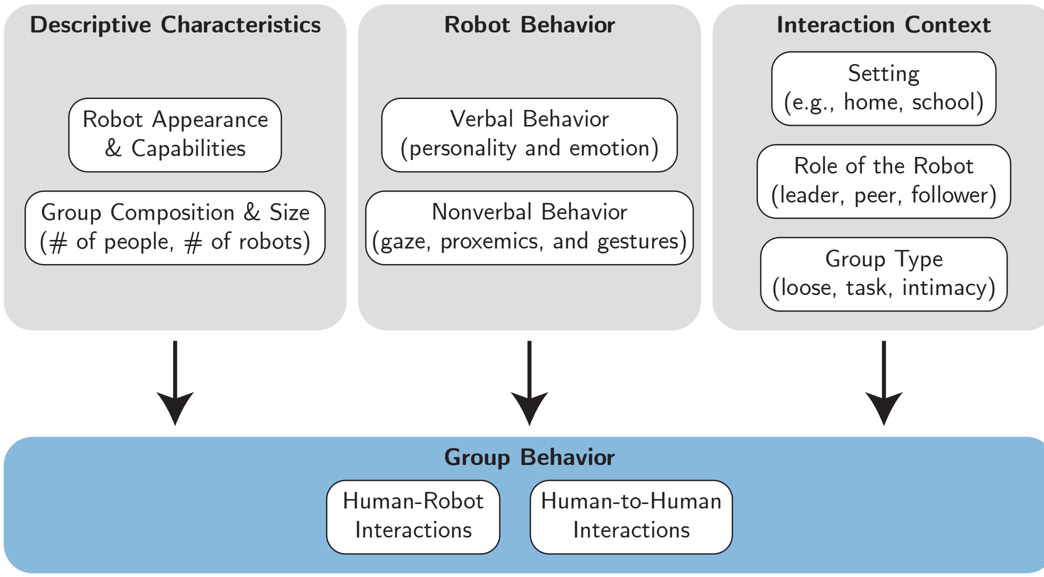

Fig. 7. Based on our analysis of the studies included in this review, we highlight three factors (descriptive characteristics, robot behavior, and interaction context) that explain how a robot's actions can influence the behavior of a human-robot group.

(loose, task intimacy). Finally, in Section 3.4 we analyzed some of the effects of robots on group behavior, highlighting work that has demonstrated that robots can influence how people in the group interact *with one another* (i.e., human-to-human interactions). We hope that this framework can serve as a guide for future research that investigates how robots can best be designed to interact with human groups and teams.

4 DISCUSSION

We have presented a review of studies that examined robots in group contexts highlighting specifically the key descriptive characteristics of robots and human-robot groups, the impact of nonverbal and verbal robot behavior, the key contextual factors that influence human-robot group interactions, and the effect of a robot's actions on how people interact with each other. The contributions made by studies of robots in groups cover a range of contexts, variables, and use cases. With this in mind, we next discuss implications for theory, design, and research methods for work examining robot interactions with groups and teams of people.

4.1 Implications for Theory

As Jung and Hinds [79] have argued previously, it is important to build theory about a robot's impact in complex social situations such as group contexts. Research on human robot interactions has only recently focused on groups as an explicit area of shared concern and no broadly accepted theories have been developed that capture a robot's impact on groups and teams. In contrast, CSCW research began almost 40 years ago with the premise that it is important to depart from a "one person and one computer" focus towards a focus on understanding "how technology could support groups, organizations, and communities" [62]. However, to date, efforts to theorize a robots role and impact within a group or team are scarce, despite some exceptions (e.g. [2, 150, 194]).

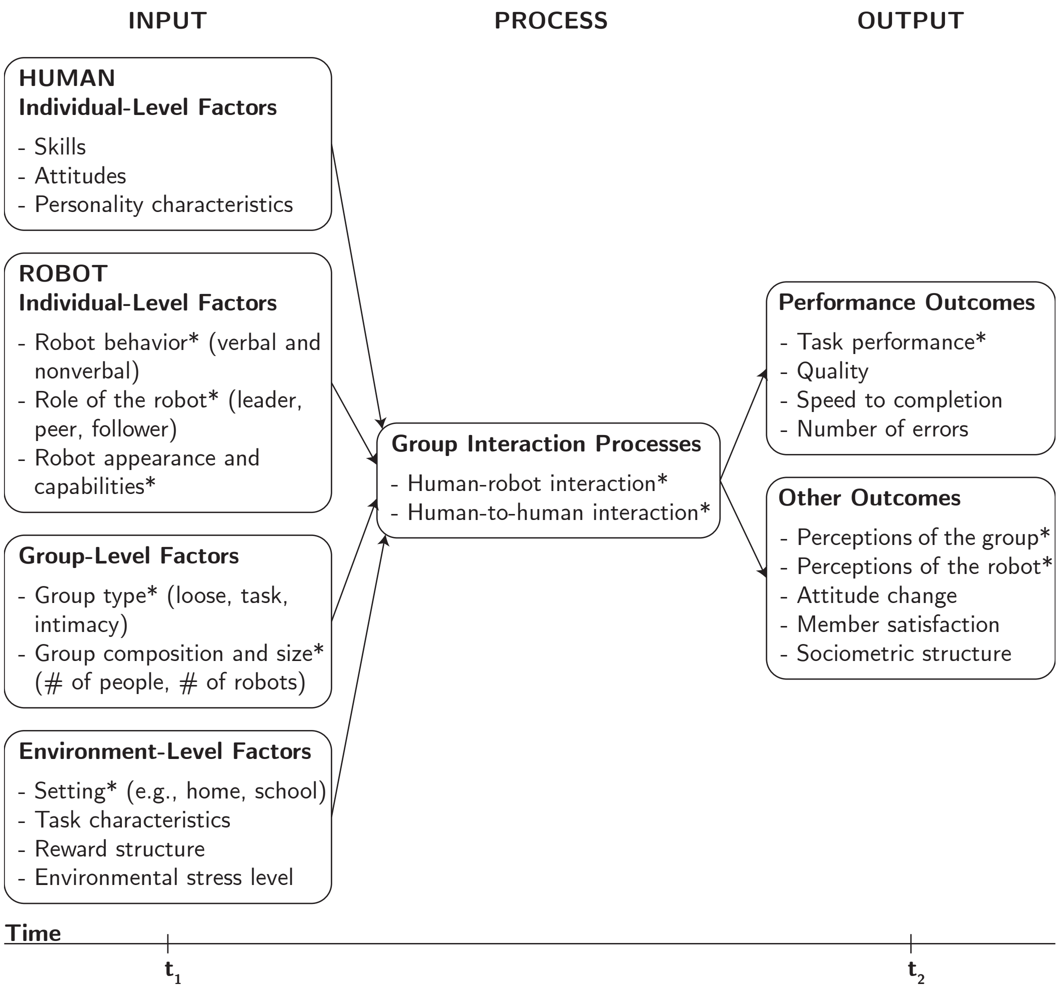

Fig. 8. Human-Robot Group IPO Framework: An input-process-output framework describing robot interactions with a group or team of people, adapted from [64, 119]. The factors specifically discussed in this paper are denoted with an asterisk (*).

Building on the findings from this review that robots influence groups to a large degree by influencing interactions among people and robots, we propose a Human-Robot Group IPO Framework (Figure 8) that draws from an influential input-process-output (IPO) framework to study group interaction that was initially proposed by McGrath (1964) [119] and later adapted by Hackman and Morris (1975) [64]. The framework places a group's interaction process as a mediator between several input factors and a group's outcomes. It conceptualizes a robot (its behavior and role within a group) as an input factor to a group's interaction process. By "interaction process" we refer to all observational interaction behavior among people and robots that occurs between two arbitrary points in time (tl and t2). The fundamental assumption underlying the framework is that "input factors affect performance outcomes through the interaction process" [64] (p.6).

This framework considers individual-level, group-level, and environment level factors that shape group interaction process and, afterwards, affect the outcomes of the group or team. Within the framework, we have included the robot-related factors that we have highlighted in Section 3 of this review, denoted as asterisks (*), in Figure 8.

With this framework in mind, we discuss what the field as a whole has learned from existing work by focusing on four questions: 1) How can we conceptualize a robot as part of a group or team? 2) To what degree does what we know about interactions between one robot and one person scale to interactions between one or more robots and groups of people? 3) What have we learned about a robot's impact on groups? and 4) To what degree does what we know about purely human groups apply to mixed human-robot groups?

4.1.1 How can we conceptualize a robot as part of a group or team? A perspective on technology that has been embraced by CSCW and HRI researchers alike (despite some reservations, e.g., [42]) is the computers as social actors (CASA) theory (e.g., [130, 138]). CASA posits that people mindlessly rely on social script and heuristics when responding to machines [130, 138]. CASA theory stresses that social responses to machines are independent of the conceptualization of a machine as human-like. For example, Nass and Moon [130] report that during their many studies "not a single participant has ever said that a computer should be understood in human terms or should be treated as a person" (p.82). While CASA theory helps us understand how people respond to robots, it does not explicitly address questions about how people make sense of a robot as a member of a group.

Research in CSCW has conceptualized technology predominantly as a tool [96] or infrastructure [122] based on which groups and teams interact and perform. With that focus on tools and infrastructure, time (e.g., synchronous vs asynchronous) and place (e.g., face-to-face vs. electronic) have been consistently highlighted as dimensions that are among the most relevant when theorizing the impact a technology has on groups and teams [61, 75]. The focus on time and place has remained even as CSCW has moved to what Wallace and colleagues [187] call the "Post-PC Era" and broadened its scope to include technologies other than the PC [96]. A robot as tool or infrastructure perspective does, however, not capture how most of the research examined here conceptualizes robots within a group or team, where robots are viewed as agents that can act independently.

In contrast to CSCW, research in HRI has rarely conceptualized robots as tools or infrastructure and has instead theorized robots predominantly as peers, communication partners or teammates [137]. For example, Fischer argues that it is important "to make collaborative robots social, and even emotional, actors if we want collaboration to succeed" [43]. Departing from a conceptualization of technology as a tool has made characteristics and dimensions other than time and place more relevant when theorizing this technology. In particular, HRI research has focused on understanding when and why people treat a robot in human-like ways (e.g., [42, 87]) and consequently focused on aspects such as the type and degree of mind perception [189], anthropomorphism [37, 87], or the tendency to apply an intentional stance [114] towards a robot. This focus on robots as a social constituent member of a group rather than a tool is reflected by our findings that highlight the influence of a robot's individual-level factors (robot behavior, robot role, robot appearance and capabilities) on a group or team, as shown in Figure 8.

Although earlier work questioned whether a robot can and should be considered a teammate [60], current research in HRI has predominately adopted the premise that robots can be group members. Under this assumption, further work has sought to understand the factors that determine how people make sense of a robot within a group or team. For example, a recent paper by Abrams and Rosenthal von der Pütten [2] proposed the I-C-E framework to distinguish between Ingroup Identification, Cohesion and Entitativity in developing understanding about a robot's positioning within a group from an individual or group level perspective. The Human-Robot Group IPO Framework introduced in Figure 8 builds on the notion of a robot as a constituent member of a group but conceptualizes a robot (its behavior and role within a group) as an input factor to a group's interaction process and therefore shifts the focus towards understanding how robots shape group dynamics and outcomes over time.

4.1.2 To what degree does what we know about interactions between one robot and one person scale to interactions between one or more robots and groups of people? Work included in our review shows consistent evidence that robot interactions with a single person do not well extend to interactions with groups of people (see Section 1.1). People have demonstrated an increased likelihood to converse with a robot receptionist in groups rather than as individuals, and also had longer conversations with the robot receptionist when in groups [56, 120]. Children have demonstrated lower retention of educational material when interacting with a robot in a group of children as opposed to interacting with a robot one-on-one [100, 101]. People are also more likely to comply with the requests of a robot when they are in a group, as opposed to when they are alone [18]. Lastly, groups of people are more likely than individuals to exhibit competitive [24, 52] and abusive [17, 20, 143] behavior towards robots.

4.1.3 What have we learned about a robot's impact on groups? Our review has shown that a robot can have a profound impact on a group through its behavior, role within a group, and its appearance and capabilities (Figure 8). Most importantly, research has shown that a robot's verbal and non-verbal behavior can extend to shape how the people in a group interact not only with the robot but also with each other, i.e., human-to-human interactions. For example, Strohkorb Sebo and colleagues [164] documented what they called a "ripple effect" of a robot's behavior within a group. Vulnerable expressions made by a robot turned out to be socially contagious as it led to increased pro-social behavior among group members. Another study has shown that such ripple effects extend to simple interactive smart speakers as their behavior has been shown to increase social cohesion within families [97]. Other recent work has shown that even the mere presence of a robot can shape people's interpersonal interactions with each other [35]. Building understanding about a robot's impact on interpersonal dynamics is essential since the way people interact with each other affects outcomes in work and non-work contexts alike (e.g., [59, 78, 80])

4.1.4 To what degree does what we know about purely human groups apply to mixed human-robot groups? Looking at existing work on groups and teams, a rich body of work comprising more than a century's worth of research has provided important understanding and theory of small groups and teams and identified focal areas of concern such as a group's ecology, structure, and composition, or key processes such as performance and conflict [104]. Much of the work captured in this review has supported the prior work in groups and teams of people, extending the same principles to human-robot groups and teams. This is especially true in work that supports the notion that robots can be theorized as filling the role of a human group member [31, 164].

However, this current understanding relies on studies that have predominantly used robots with highly anthropomorphic physical features (e.g., a head, eyes, hands) and employing very human-like modalities of interaction (e.g., speech) such as Robovie (16% of studies) and Nao (15% of studies). It is thus less clear if findings hold for less anthropomorphic robots such as Micbot [176], a robotic microphone devoid of anthropomorphic physical features, and Kip1 [68], a peripheral robot companion resembling a lamp. Existing evidence suggests that people indeed react differently to robotic systems based on their anthropomorphic characteristics. For example, research by Malle and colleagues showed that people apply different moral reasoning to robots than to humans [112]. However, a later study showed that the effect only applies to non-anthropomorphic system as people applied the same reasoning to anthropomorphic robots that they apply to humans [113]. We encourage researchers to pursue work understanding the influence of and building the appropriate theory for non-anthropomorphic robots that shape human group interactions in unique ways.

In summary, the literature provides compelling evidence that 1) robots cannot simply be conceptualized as tools or infrastructure, but also are not always viewed similarly to people, 2) people interact differently with robots when they are alone than when they are with other people, 3) that a robot's behavior impacts how people interact with each other, and 4) that while current findings on group effects are consistent with theory on human-only groups, it might be premature to assume that this is always the case given that most research up to this point relied on anthropomorphic robotic systems. Additionally, we have presented a human-robot group IPO framework (Figure 8) that encapsulates the unique contributions and influence robots have in groups and teams.

4.2 Implications for Design

Considering groups and teams explicitly requires new approaches for many facets of robot design, including the tasks and roles robots adopt, the computational models robots use when interacting with people, and unique group affordances robots can utilize.

As we develop a broader understanding of robots in groups and teams, it is important to identify the types of group tasks that robots are uniquely positioned to excel in compared to their human counterparts. Groom and Nass [60] suggest that one of the key determinants of having robots as successful teammates is in identifying and leveraging the unique strengths that robots bring to groups. From our analysis of the roles (leader, peer, follower) robots take on in specific contexts (Figure 5), we have begun to see trends that suggest that there do exist roles within groups of people that robots can uniquely fill, and in doing so, bring value to the group. As work continues in this field, it is critical that we remain focused on investigating the *unique* value that robots bring to interactions with groups of people in a variety of contexts.

When developing mathematical models for robots to sense relevant human characteristics as well as make decisions within the context of a group, the design of new approaches and models is essential. The work of Leite et al. (2015) highlights this problem well in the space of detecting disengagement in children. They found that machine learning models trained to reliably detect disengagement in individual children did not extend to children in the context of a peer group [102]. In order to build computational models that are successful in group contexts, special care must be taken to adapt these models to behaviors exhibited in human groups.

Finally, from a design perspective, groups offer specific affordances such as their leadership structure or network that robots can exploit when interacting with groups. For example, Kwon and Sadigh [95] proposed an approach for a robot to make inferences about the underlying leadership structure of a group and showed that a robot can leverage that structural understanding to influence how the group behaves. Further, Shirado and Christakis [156] showed that an artificial agent can improve the collective performance of groups when placed at strategic locations within a network. These examples show that groups not only require new techniques but also offer new opportunities for interaction.

4.3 Implications for Research Methods

Since this field is young and growing, there are many group compositions that remain sparsely explored and could benefit from further research. As Figure 4(a) displays, few studies have investigated the influence and effects of multiple robots interacting with groups of people. Involving multiple robots in human-robot group interactions can be extremely valuable in educational contexts where children learn by watching multiple robots interacting [100, 101], in laboratory settings where multiple robot characters can be evaluated in the same group [31, 32, 133], and in interactions with children where the addition of another social robot agent can lead to increased engagement [181]. Especially in light of the recent work demonstrating that individual people conform their behavior to groups of robots [142, 183], more work investigating the use of multiple robots when interacting with groups of people is important and useful to this area of research.

Additionally, research investigating robots interacting with groups of people has primarily focused on short-term interactions and has not thoroughly explored long-term interactions. 75% of the experimental studies contained within this review were conducted for a single experimental session, as shown in Figure 3(c). Single session studies may be useful for evaluating the influence of particular robot behaviors on groups of people in short-term interaction contexts (e.g., advertising robots in a shopping mall, mail delivery robots). However, in the future we will most likely interact with robots repeatedly over weeks, months, and years (e.g., household assistant robots, delivery robots in the workplace, robot tutors), that build relationships with us and adapt their behavior to us over time. In order to explore the influence of robots on groups of people in the real-world contexts they are beginning to inhabit, it is essential that more long-term and multiple-session human-subject research studies are conducted.

As research investigating robots interacting with groups of people continues to grow, more rigorous and comprehensive methods and measures must be developed to help capture the impact of robots interacting with groups of people. The methods and measures that are most closely applicable, from the fields of human-robot interaction and organizational psychology, do not quite fit when applied to robots interacting with groups of people. For example, in organizational psychology group-level phenomena like cohesion is measured by administering questionnaires to company employees. For robots interacting with groups, it would be helpful if a robot could measure group cohesion through observing the real-time behavior of group members, so that the robot could adapt its actions based on the current cohesion of the group, rather than having to rely on an infrequently administered questionnaire.

5 CONCLUSION

As robots interact with people in increasingly complex settings, with more diverse roles, and over longer periods of time, these interactions will rarely resemble the dyadic interactions historically studied in the field of human-robot interaction. The body of work highlighted in this review has taken some first steps in the direction of equipping robots with the abilities to interact with groups of people, often in complex field settings, and studying the effects of robot actions. As researchers in this field work to address the current technical and methodological challenges involved with group interactions, we can work to develop and study robots that richly interact with many groups over long periods of time in natural environments.

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A RESEARCH STUDIES INCLUDED IN THIS REVIEW

In this review, we included 103 papers that detailed 101 distinct participant studies (please refer to Section 2 for details on our inclusion criteria and method for selecting these studies). In Table 1 we list each of the studies as well as their references and categorized attributes.

Table 1. For each of the studies included in this review, in this table we list their reference, the robot(s) used in the study and whether or not they have a head and eyes, the country where the study took place, the setting of the study, the robot control paradigm (autonomous or wizard of oz - WoZ), the role of the robot, the composition of the human-robot group, the human group type [109], the main robot behavior(s) examined in the study, the study design type, the number of between subject conditions (N_{BSC}), the number of experimental groups (N_G), the number of human participants (N_P), and the number of experimental sessions (N_S).

ID	Reference	Robot(s) Used (Head & Eyes?)	Country	Study Setting	Robot Control	Robot Role	Group Composition(s)	Group Type	Main Robot Behavior(s) Examined	Study Design Type	N_{BSC}	N_G	N_P	N_S
1	Ablett et al. (2007) [1]	Aibo (yes)	Canada	lab	autonomous	leader	1 robot 7 people	task	locomotion	observation-based	1	2	14	2
2	Alemi et al. (2016) [3]	Nao (yes)	Iran	field (hospital)	WoZ	peer	1 robot 6 people	loose	emotion	experimental	2	2	11	8
3	Alemi et al. (2015) [4]	Nao (yes)	Iran	field (school)	WoZ	leader	1 robot 15 people	task	content delivery	experimental	2	3	46	10
4	Alves-Oliveira et al. (2015) [6]	Nao torso (yes)	Portugal	field (school)	WoZ	leader	1 robot 2 people	task	emotion	experimental	1	28	56	1
5	Alves-Oliveira et al. (2016) [7]	Nao torso (yes)	Portugal	field (school)	autonomous	leader	1 robot 2 people	task	emotion	experimental	3	25	50	1
6	Baddoura and Venture (2013) [11]	Nao (yes)	Japan	lab	autonomous	leader	1 robot 2 people	loose	gestures	experimental	1	20	40	1
7	Ball et al. (2017) [13]	Custom (no)	Australia	lab	WoZ	peer	1 robot 2 people	task	locomotion	experimental	4	70	140	1
8	Booth et al. (2017) [18]	Turtlebot (no)	USA	field (public area)	WoZ	peer	1 robot varied people	loose	content delivery	experimental	3	72	108	1
9	Brscic et al. (2015) [20] (study 1/2)	Robovie (yes)	Japan	field (shopping mall)	WoZ	leader	1 robot varied people	loose	locomotion	experimental	1	185	–	1
10	Brscic et al. (2015) [20] (study 2/2)	Robovie (yes)	Japan	field (shopping mall)	autonomous	leader	1 robot varied people	loose	locomotion	experimental	2	57	–	1
11	Chandra et al. (2015) [21]	Nao torso (yes)	Portugal	field (school)	WoZ	leader	1 robot 2 people, 3 people	task	content delivery	experimental	2	20	40	1
12	Chandra et al. (2016) [22]	Nao torso (yes)	Portugal	field (school)	WoZ	leader	1 robot 2 people	task	content delivery	experimental	2	20	40	1
13	Chang et al. (2013) [23]	PARO (yes)	USA	field (elder care facility)	autonomous	follower	1 robot varied people	loose	emotion	observation-based	1	1	10	7
14	Chang et al. (2012) [24]	iRobot Create (no)	USA	lab	WoZ	peer	1 robot 2 people, 2 robots 2 people, 1 robot 1 person, 2 robots 1 person	task	locomotion	experimental	4	31	41	1
15	Correia et al. (2016) [29] (study 1/2)	EMYS (yes)	Portugal	lab	autonomous	peer	1 robot 3 people	task	content delivery	experimental	1	20	60	1
15	Correia et al. (2017a) [30]	EMYS (yes)	Portugal	lab	autonomous	peer	1 robot 3 people	task	content delivery	experimental	1	20	60	1
16	Correia et al. (2016) [29] (study 2/2)	EMYS (yes)	Portugal	field (public area)	autonomous	peer	1 robot 3 people	task	content delivery	experimental	1	5	17	1
17	Correia et al. (2018) [31]	EMYS (yes)	Portugal	lab	autonomous	peer	2 robots 2 people	task	emotion	experimental	1	24	48	1
18	Correia et al. (2017b) [32] (study 1/2)	EMYS (yes)	Portugal	lab	autonomous	peer	1 robot 3 people	task	personality	experimental	2	10	30	1
18	Correia et al. (2019) [33] (study 1/2)	EMYS (yes)	Portugal	lab	autonomous	peer	1 robot 3 people	task	personality	experimental	2	10	30	1
19	Correia et al. (2017b) [32] (study 2/2)	EMYS (yes)	Portugal	lab	autonomous	peer	2 robots 2 people	task	personality	experimental	1	31	61	1
19	Correia et al. (2019) [33] (study 2/2)	EMYS (yes)	Portugal	lab	autonomous	peer	2 robots 2 people	task	personality	experimental	1	31	61	1
19	Oliveira et al. (2018) [133]	EMYS (yes)	Portugal	lab	autonomous	peer	2 robots 2 people	task	personality	experimental	1	30	60	1

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20	Faria et al. (2017) [39]	Baxter (yes)	Portugal	lab	autonomous	follower	1 robot 3 people	loose	gestures	experimental	1	11	33	1
21	Fernández-Llamas et al. (2017) [41]	Baxter (yes)	Spain	field (school)	autonomous	leader	1 robot 10 people	task	content delivery	experimental	2	–	190	1
22	Forlizzi (2007) [45]	Roomba (no)	USA	field (home)	autonomous	follower	1 robot varied people	intimacy	locomotion, content delivery	observation-based	2	6	23	–
23	Forlizzi and DiSalvo (2006) [46]	Roomba (no)	USA	field (home)	autonomous	follower	1 robot varied people	intimacy	locomotion, content delivery	observation-based	1	~7	–	–
24	Fortunati et al. (2018) [48]	DORO (yes)	Italy	field (public area)	autonomous	follower	1 robot varied people	loose	gestures, content delivery	experimental	3	3	174	1
25	Foster et al. (2012) [49]	iCat with two arms (yes)	UK	lab	autonomous	follower	1 robot 2 people, 1 robot 1 person	loose	content delivery	experimental	1	31	31	1
26	Fraune et al. (2019) [52]	Beam (yes)	USA	lab	WoZ	peer	1 robot 3 people, 1 robot 1 person, 3 robots 3 people, 3 robots 1 person	task	content delivery	experimental	4	81	105	1
27	Fukuda et al. (2016) [53]	Robovie (yes)	Japan	lab	autonomous	leader	1 robot 3 people, 4 people	loose	content delivery	experimental	1	40	120	1
28	Gehle et al. (2015) [55]	Nao (yes)	Germany	field (museum)	autonomous	leader	1 robot varied people	loose	content delivery	observation-based	1	55	–	1
29	Gockley et al. (2006) [56]	Robocep-tionist (yes)	USA	field (public area)	autonomous	follower	1 robot varied people	loose	emotion	experimental	3	~1000	2679	1
30	Gombolay et al. (2015) [57]	PR2 (yes)	USA	lab	autonomous	leader, peer, follower	1 robot 2 people, 3 people	task	content delivery	experimental	2	48	48	1
31	Hebesberger et al. (2016) [66]	SCITOS G5 (yes)	Austria	field (elder care facility)	autonomous	leader	1 robot 7 people	loose	locomotion, content delivery	observation-based	1	2	14	13
32	Hoffman et al. (2015) [68]	Kip1 (no)	Israel	lab	autonomous	leader	1 robot 2 people	intimacy	gestures	experimental	2	30	60	1
33	Hood et al. (2015) [69]	Nao (yes)	Switzer-land	field (school)	autonomous	peer	1 robot 8 people, 1 robot 2 people, 1 robot 1 person	task	content delivery	observation-based	1	18	53	1
34	Hyun and Yoon (2009) [70]	iRobiQ (yes)	South Korea	field (child care center)	autonomous	peer	1 robot varied people	intimacy	content delivery	observation-based	1	2	43	–
35	Imai et al. (2002) [72]	Robovie (yes)	Japan	lab	autonomous	peer	1 robot 7 people	loose	gaze	experimental	1	5	36	1
36	Iqbal et al. (2016) [73]	Turtlebot (no)	USA	lab	autonomous	peer	1 robot 3 people	task	locomotion	experimental	1	9	27	1
37	Iqbal and Riek (2017) [74]	Turtlebot (no)	USA	lab	autonomous	peer	1 robot 3 people, 2 robots 3 people	task	locomotion	experimental	1	6	18	1
38	Johansson et al. (2013) [76]	Furhat (yes)	Sweden	lab	WoZ	peer	1 robot 2 people	task	gaze	experimental	1	4	8	1
39	Joshi and Šabanović (2019) [77]	PARO, Nao, Joy, Cozmo (yes - all)	USA	field (elder care facility)	WoZ, autonomous	follower	1 robot varied people	loose	gestures, emotion, locomotion	observation-based	5	12	74	12
40	Jung et al. (2015) [81]	Custom	USA	lab	WoZ	peer	1 robot 3 people	task	content delivery	experimental	4	53	106	1
41	Kanda et al. (2004) [82]	Robovie (yes)	Japan	field (school)	autonomous	leader	1 robot varied people	loose	personality	experimental	1	2	228	9
42	Kanda et al. (2007) [83]	Robovie (yes)	Japan	field (school)	autonomous	peer	1 robot varied people	loose	personality	experimental	1	1	37	32
43	Kanda et al. (2012) [84]	Robovie (yes)	Japan	field (school)	WoZ	leader	1 robot 4 people	task	personality	experimental	2	8	31	8

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44	Kidd et al. (2006) [85]	PARO (yes)	USA	field (elder care facility)	autonomous	follower	1 robot 5 people	loose	emotion	observation-based	1	2	23	6
45	Kidokoro et al. (2013) [86]	Robovie (yes)	Japan	field (shopping mall)	autonomous	peer	1 robot varied people	loose	locomotion	experimental	2	–	3583, 90	1
46	Kim et al. (2013) [88]	Pleo (yes)	USA	lab	WoZ	peer	1 robot 2 people	task	emotion	experimental	1	24	24	1
47	Kirchner et al. (2011) [89]	Robot-Assist (yes)	Australia	field (public area)	autonomous	leader	1 robot varied people	loose	gaze	experimental	2	64	456	1
48	Kochigami et al. (2018) [90]	Pepper, Nao (yes - both)	Japan	lab	autonomous	leader	2 robots 14 people	loose	content delivery	experimental	1	1	14	1
49	Kondo et al. (2013) [91] (study 1/2)	Android-SIT (yes)	Japan	field (museum)	autonomous	leader	1 robot varied people	loose	gestures	experimental	4	–	1662	1
50	Kozima et al. (2005) [92]	Keepon (yes)	Japan	field (child care center)	WoZ	peer	1 robot varied people	intimacy	gaze, emotion	observation-based	1	2	5	27
51	Leite et al. (2016) [99]	Keepon (yes)	USA	field (school)	autonomous	peer	2 robots 3 people	intimacy	content delivery	experimental	3	24	72	3
52	Leite et al (2015a) [100]	Keepon (yes)	USA	field (school)	autonomous	peer	2 robots 3 people, 2 robots 1 person	intimacy	emotion	experimental	2	30	40	3
52	Leite et al. (2017) [101]	Keepon (yes)	USA	field (school)	autonomous	peer	2 robots 3 people, 2 robots 1 person	intimacy	emotion	experimental	2	30	40	3
52	Leite et al (2015b) [102]	Keepon (yes)	USA	field (school)	autonomous	peer	2 robots 3 people, 2 robots 1 person	intimacy	emotion	experimental	2	30	40	3
53	Leite et al (2012) [103]	iCat (yes)	Portugal	lab	autonomous	peer	1 robot 2 people	task	emotion	experimental	1	20	40	1
54	Li et al. (2016) [108]	Tangy (yes)	Canada	field (elder care facility)	autonomous	leader	1 robot 7 people	loose	personality, content delivery	experimental	1	1	7	6
55	Liu et al. (2013) [110]	Robovie (yes)	Japan	field (shopping mall)	WoZ	peer	1 robot 3 people	loose	gestures	experimental	1	26	33	1
56	Ljungblad et al. (2012) [111]	Custom (no)	Sweden	field (hospital)	autonomous	follower	1 robot varied people	task	locomotion, content delivery	observation-based	1	1	25	–
57	Matsuzoe et al. (2014) [117]	Nao (yes)	Japan	field (school)	autonomous	peer	1 robot 7 people	intimacy	personality, content delivery	experimental	2	2	15	4
58	Mavrogiannis et al. (2019) [118]	Beam (yes)	USA	lab	autonomous	leader	1 robot 3 people	task	locomotion	experimental	1	35	105	1
59	Michalowski et al. (2007) [121]	RWI B21 (yes)	USA	field (public area)	autonomous	leader	1 robot varied people	loose	locomotion, content delivery	experimental	1	171	–	1
60	Moshkina et al. (2014) [124]	Xitome humanoid (yes)	USA	field (public area)	autonomous	leader	1 robot varied people	loose	gestures	experimental	8	123	4222	1
61	Mutlu and Forlizzi (2008) [126]	Aethon TUG (no)	USA	field (hospital)	autonomous	follower	1 robot varied people	task	locomotion, content delivery	observation-based	1	3	–	–
62	Mutlu et al. (2006) [127]	ASIMO (no)	USA	lab	autonomous	leader	1 robot 2 people	loose	gaze	experimental	1	10	20	1
63	Mutlu et al. (2009) [128]	Robovie (yes)	Japan	lab	WoZ	leader	1 robot 2 people	loose	gaze	experimental	3	36	72	1
64	Nabe et al. (2006) [129]	Robovie (yes)	Japan	field (museum)	autonomous	leader	1 robot varied people	loose	locomotion	experimental	1	~70	238	1
65	Oliveira et al. (2019) [134]	EMYS (yes)	Portugal	lab	autonomous	peer	2 robots 2 people	task	personality	experimental	4	27	54	1
66	Pereira et al. (2010) [136]	iCat	Portugal	lab	autonomous	peer	1 robot 2 people	task	emotion	experimental	1	5	10	1
67	Šabanović et al. (2013) [139]	PARO (yes)	USA	field (elder care facility)	autonomous	follower	1 robot varied people	loose	emotion	experimental	1	1	7	7
68	Sabelli and Kanda (2016) [140]	Robovie (yes)	Japan	field (shopping mall)	WoZ	follower	1 robot varied people	loose	content delivery	observation-based	1	1	67	–
69	Sabelli et al. (2011) [141]	Robovie (yes)	Japan	wild (elder care facility)	WoZ	peer	1 robot varied people	loose	personality	observation-based	1	1	55	–

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70	Salvini et al. (2010) [143]	Piero (no)	South Korea	field (public area)	autonomous	leader	1 robot varied people	loose	locomotion, content delivery	observation-based	1	–	–	1
71	Sauppé and Mutlu (2015) [144]	Baxter (yes)	USA	field (manufacturing plant)	autonomous	follower	1 robot varied people	task	content delivery	observation-based	1	3	–	–
72	Scassellati et al. (2018) [145]	Jibo (yes)	USA	field (home)	autonomous	leader	1 robot 2 people	intimacy	personality, content delivery	experimental	1	~24	12	23
73	Sequeira et al. (2016) [146]	Nao torso (yes)	Portugal	field (school)	autonomous	leader	1 robot 2 people	task	emotion	experimental	3	39	78	1
74	Shamekhi et al. (2018) [148]	Beam (yes)	USA	lab	WoZ	leader	1 robot 2 people	task	content delivery	experimental	2	20	40	1
75	Shen et al. (2018) [149]	Keepon (yes)	USA	lab	WoZ	leader	1 robot 2 people	intimacy	content delivery	experimental	2	32	64	1
76	Shimada et al. (2011) [152] (study 1/2)	Android Repliee Q2 (yes)	Japan	lab	WoZ	follower	1 robot 2 people	task	gaze	experimental	2	30	30	1
77	Shimada et al. (2011) [152] (study 2/2)	Android Repliee Q2 (yes)	Japan	lab	WoZ	follower	1 robot 2 people	task	gaze	experimental	2	30	30	1
78	Shiomi et al. (2015) [153]	Robovie (yes)	Japan	field (school)	WoZ	peer	1 robot varied people	loose	personality, content delivery	experimental	1	4	114	12
79	Shiomi et al. (2010) [154]	Robovie (yes)	Japan	field (shopping mall)	autonomous	leader	1 robot varied people	loose	locomotion	experimental	3	37	269	1
80	Shiomi et al. (2007) [155]	Robovie (yes)	Japan	field (museum)	WoZ	leader	1 robot varied people	loose	locomotion	experimental	1	–	120	1
81	Short and Matarić (2017) [157]	SPRITE (yes)	USA	lab	autonomous	leader	1 robot 3 people	task	content delivery	experimental	1	10	30	1
82	Short et al. (2017) [158]	SPRITE (yes)	USA	lab	autonomous	peer	1 robot 3 people	intimacy	personality, content delivery	experimental	1	6	18	1
83	Skantze (2017) [160]	Furhat (yes)	Sweden	field (museum)	autonomous	leader	1 robot 2 people	task	gaze	experimental	1	270	540	1
83	Skantze et al. (2015) [161]	Furhat (yes)	Sweden	field (museum)	autonomous	leader	1 robot 2 people	task	gaze	experimental	1	373	746	1
84	Strohkorb et al. (2016) [163]	Keepon (yes)	USA	field (school)	autonomous	leader	1 robot 2 people	task	content delivery	experimental	3	43	86	1
85	Strohkorb Sebo et al. (2018) [164]	Nao (yes)	USA	lab	autonomous	peer	1 robot 3 people	task	personality	experimental	2	35	105	1
86	Sung et al. (2010) [166]	Roomba (no)	USA	field (home)	autonomous	follower	1 robot varied people	intimacy	locomotion, content delivery	observation-based	1	30	70	–
87	Taheri et al. (2018) [167]	Alice R50, Nao (yes-both)	Iran	lab	WoZ	leader	1 robot 5 people, 2 robots 5 people	task	personality, content delivery	experimental	1	3	15	12
88	Tahir et al. (2018) [168] (study 2/2)	Nao (yes)	Singapore	lab	autonomous	leader	1 robot 2 people	loose	personality	experimental	1	10	20	1
89	Tan et al. (2018) [173]	Cozmo (yes)	USA	lab	autonomous	peer	1 robot 2 people	loose	emotion	experimental	6	48	48	1
90	Tanaka et al. (2007) [174]	QRIO (yes)	USA	field (child care center)	WoZ	peer	1 robot varied people	intimacy	personality	experimental	1	1	12	45
91	Tennent et al. (2019) [176]	Micbot (no)	USA	lab	autonomous	leader	1 robot 3 people	task	gestures	experimental	3	36	108	1
92	Thompson et al. (2017) [177]	Tangy (yes)	Canada	field (elder care facility)	autonomous	leader	1 robot 6 people	loose	personality, content delivery	experimental	1	1	6	2
93	Utami and Bickmore (2019) [178]	Furhat (yes)	USA	lab	autonomous	leader	1 robot 2 people	intimacy	content delivery	experimental	1	12	24	1
94	Vázquez et al. (2017) [179]	Chester and Blink (yes-both)	USA	lab	WoZ	leader	1 robot 3 people	task	gaze	experimental	4	20	69	1
95	Vázquez et al. (2011) [180]	Custom (no)	USA	lab	autonomous	leader	1 robot 4 people	loose	content delivery	experimental	1	6	24	1

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96	Vázquez et al. (2014) [181]	Chester and Blink (yes-both)	USA	lab	WoZ	leader	1 robot 4 people, 2 robots 4 people	loose	personality	experimental	2	20	74	1
97	Wada et al. (2005) [184]	PARO (yes)	Japan	field (elder care facility)	autonomous	follower	1 robot varied people	loose	emotion	experimental	1	1	14	–
98	Wada et al. (2004) [185]	PARO (yes)	Japan	field (elder care facility)	autonomous	follower	1 robot varied people	loose	emotion	experimental	1	1	23	15
99	Wang et al. (2010) [188]	Custom (unclear)	China, USA	lab	WoZ	peer	1 robot 2 people	task	personality	experimental	4	160	320	1
100	Yamazaki et al. (2012) [193]	Robovie (yes)	Japan	field (museum)	autonomous	leader	1 robot 3 people	loose	content delivery	experimental	1	31	71	1
101	Zubrycki and Granosik (2016) [196]	Robot Ono (yes)	Poland	field (therapist office)	WoZ	follower	1 robot 2 people	task	content delivery	observation-based	1	7	14	1