How Robots Influence Humans: A Survey of Nonverbal Communication in Social Human–Robot Interaction

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Abstract
As robots become more prevalent in society, investigating the interactions between humans and robots is important to ensure that these robots adhere to the social norms and expectations of human users. In particular, it is important to explore exactly how the nonverbal behaviors of robots influence humans due to the dominant role nonverbal communication plays in social interactions. In this paper, we present a detailed survey on this topic focusing on four main nonverbal communication modes: kinesics, proxemics, haptics, and chronemics, as well as multimodal combinations of these modes. We uniquely investigate findings that span across these different nonverbal modes and how they influence humans in four separate ways: shifting cognitive framing, eliciting emotional responses, triggering specific behavioral responses, and improving task performance. A detailed discussion is presented to provide insights on nonverbal robot behaviors with respect to the aforementioned influence types and to discuss future research directions in this field.

Keywords Human–robot interaction · Social robots · Nonverbal communication · Influence on humans

1 Introduction

As robots become increasingly ubiquitous in environments such as our homes, workplaces, hospitals, and schools, they need to have social intelligence that enables them to effectively interact with and assist humans. Research in the field of human–robot interaction (HRI) has explored the social and functional relationships between humans and robots at the intersection of engineering, computer science, psychology, linguistics, ethology, and other disciplines [1]. In particular, such research has covered a wide breadth of social HRI applications for which robots provide assistance with healthcare (including eldercare) [2–4], education and training [5, 6], entertainment [7, 8], search and rescue [9, 10], and tour guiding in retail and museum settings [6, 11].

Within these applications, a robot's effective use of nonverbal communication can be crucial for engagement with humans as it allows for intuitive interaction between humans and robots [12]. In general, *nonverbal communication* is the unspoken dialogue that creates shared meaning in social interactions [13], which can have emotional or functional intent [14, 15]. It is a critical area of study that is estimated to encompass more than 60% of all communicated meaning in human [16–19]. Nonverbal communication is commonly categorized into a handful of distinct, but socially inter-related modes—kinesics, proxemics, haptics, chronemics, vocalics, and presentation [20]. In this paper we will focus on investigating modes that directly incorporate robot movements, namely kinesics, proxemics, haptics, and chronemics.

In contrast to vocal communication which is largely learned through more explicit experiences relevant to specific cultures, nonverbal communication through movement is a vital area of study as its origins largely arise through inherited behaviors (e.g. reflexes) or primal experiences common to all humans (e.g. the use of hands towards the mouth indicating eating) [21]. This means that these nonvocal, nonverbal forms of communication are consistent across cultures and, because they are more instinctual and involuntary, are a more truthful representation of human thoughts and emotions [20]. More specifically, kinesics is a highly

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articulate mode that some consider to be as communicative as verbal communication [22]. Proxemics enables us to identify and associate social distances with comfort and other communicated intentions [23]. Haptics explores our earliest, most elemental, and intimate modes of communication [24]. Chronemics allows us to identify and understand the tempo of human communication [25]. Beyond these four modes, we will also consider multimodal nonverbal communication that integrates two or more of these modes into an interaction.

There are a handful of survey papers that consider nonverbal communication during HRI. For example, McColl et al. [26] reviewed the recognition of human nonverbal communication for robot decision making in HRI scenarios. Other papers have only focused on one individual type of robot nonverbal communication within the aforementioned nonverbal communication types. Within kinesics this has included arm gestures [27], body movements [9], and gaze [28]; for proxemics this has included social distance [29], and social navigation [30]; and for haptics there has also been a handful of surveys [31–33]. While these survey papers typically provide a thorough technical analysis or classification of a specific robot nonverbal communication mode or type, they do not consider the interrelationships between multiple modes nor do they specifically investigate the manner in which these modes directly *influence* humans during interactions with these robots.

In this paper, we present a unique research survey which investigates the interrelationships across multiple nonverbal communication modes in an attempt to bridge findings between them. Furthermore, we focus on how such robot nonverbal behaviors *influence* humans as an outcome. Namely, we distinctly categorize influence into the four types below and aim to provide a detailed understanding of how robot nonverbal behavior can influence a person's:

1. *Cognitive Framing* A process observed in human psychology by which people develop a certain perspective or orientation on a topic [34]. We will identify how robot nonverbal behaviors influence a human's framing of a robot(s) with respect to numerous cognitive frames such as empathy, engagement, likeability, dominance, perceived intelligence, and trust.
2. *Emotion Recognition and Response* The successful identification of a robot's nonverbally displayed emotions and the potential for these to illicit a human emotional response due to phenomena such as emotion contagion: the automatic transfer of emotions between individuals [35]. We will survey research on human recognition of robot emotions via nonverbal behaviors and determine how these influence human emotional responses.
3. *Behavioral Response* A human's nonverbal behaviors as a direct response to the presence or absence of robot nonverbal cues. We will discuss research that has directly observed human behavior in response to robot nonverbal behavior in scenarios considering entrainment, synchronization, and mimicry.
4. *Task Performance* A change in the outcome of a human task or collaborative human–robot task due to robot nonverbal behaviors. We will investigate the change in task performance influenced by a robot's nonverbal behaviors with respect to metrics like reaction time, completion time, errors, accuracy, and memory.

The following sections of this survey paper are organized as follows. Sections 2–6 discuss the existing literature on kinesic, proxemic, haptic, chronemic, and multimodal nonverbal robot communication modes, their importance and how these behaviors influence users during varying HRI scenarios. Section 7 provides a detailed discussion across the different communication modes with respect to how these modes affect a person's cognitive framing, emotion recognition and response, behavioral response, and task performance. Lastly, in Sect. 7, future research directions are also discussed with respect to open research challenges.

2 Kinesics

In general, kinesics is defined as nonverbal communication through body movements, positioning, facial expressions, and gestures [19]. Kinesics is a highly articulated form of communication that contains informative capacity on par with verbal communication [22], and can communicate extensive contextual, social, and interpersonal information (situational awareness, social intent, emotional state, etc.) [36]. Kinesics-based robotics research can be categorized into: (1) arm gestures, (2) body and head movements, (3) eye gaze, and (4) facial expressions. This section will explore each of these modes and how they influence users in HRI applications.

2.1 Arm Gestures

Arm gestures are typically defined by significant movements of the limb in a way that generates an expression of feeling or rhetoric [37]. Gestures are important due to the detail and dexterity available to the arm and hand [38] allowing them to be used in communication that is deictic (pointing), iconic (representative of objects and actions), metaphoric (representative of abstract concepts), and beat (punctuating other modes) [39]. Papers surveyed here will be presented under the defined influence types of cognitive framing, emotion recognition and response, behavioral response, and task performance.

2.1.1 Cognitive Framing

Robotic arm gestures have been shown to influence many different concepts such as sympathy, liveliness, engagement, likeability, anthropomorphism, future use intent, semantic matching, and animacy.

In [40, 41], Salem et al. investigated the impact of congruency of robot gestures with speech using the humanoid ASIMO robot. The robot was controlled using a Wizard-of-Oz (WoZ) technique to implement verbal requests with three types of gestures for manipulating and transferring objects. The gestures were chosen as: (1) iconic to illustrate object properties, (2) deictic to indicate location, and (3) pantomimic to illustrate actions. Participants were presented with robot verbal requests alongside gestures that were either congruent or incongruent to the request. They found that the robot was evaluated as more sympathetic, lively, active, and engaged when it used gestures, regardless of gesture congruency. A subsequent experiment [42] by the same authors found that, in general, gestures contributed positively to perceived anthropomorphism of the robot, regardless of congruency and that incongruent gestures improved scores of likeability, human-likeness, and future use intent (desire to see the robot again) over congruent gestures. However, the incongruent gestures negatively contributed to the task completion of participants transferring objects based on the robot's request compared to congruent gestures or no gestures at all.

Aly and Tapus [43] investigated how different human personality traits would affect the perception of extroverted (more dynamic) versus introverted (more subdued) robot gestures. They placed participants in a room with a NAO robot who provided detailed information about a restaurant's menu, service, and atmosphere while using the two different gesture behaviors. They found that the more dynamic robot gestures led to more engaging interactions and higher perceived semantic matching. In addition, when comparing participant personalities, extraverted participants preferred these dynamic gestures more than the introverted participants.

Shen et al. [44] investigated the influence of gesture coordination on framing and perceptions of the KASPAR2 humanlike robot. They instructed participants to stand in front of the robot, and perform one of three gestures (circle, triangle, or infinity symbol) using a Wii remote. As the participant began to perform the gesture, the robot would also initiate the same gesture in one of two conditions: move at a constant speed or adapt its speed to move synchronously with the participant. Their findings show that in the adaptive condition, participants rated the robot higher on gesture recognition, performance, and social interaction.

In [45], the effects of gesture style on perceptions of a robot's warmth, competence, dominance, and affiliation were investigated. A NAO humanoid robot gave a 10-min lecture on robots to children and was programmed to display four different gesture conditions of either low or high warmth and low or high competence. The development of these gestures was guided by the Interpersonal Circumplex model [46] and the Stereotype Content Model [47]. Their results showed that the two high-competence conditions led to higher participant perceptions of competence, however, warmth was perceived as high during the high warmth–high competence condition and the low warmth-low competence condition. Affiliation was rated highest for the high warmth–high competence condition, followed by the low warmth–low competence condition, the high warmth-low competence condition, and finally the low warmth–high competence condition. Dominance was also perceived highest for the high warmth–high competence condition, followed by the high warmth–low competence condition, the low warmth–low competence condition, and finally the low warmth–high competence condition.

2.1.2 Emotion Recognition and Response

With respect to emotion recognition and response, different robot emotion-based arm gestures have been investigated including comparisons between varying arm types as well as how the recognition of these emotional gestures (or inability to) may affect the emotional state of users.

Xu et al. [48] presented a 30 min lecture to a crowd of people using a NAO robot gesturing along with its lecture under two different mood conditions: positive and negative. The lecture and types of gestures used in the two conditions were the same, however, the appearance of the gestures was changed to convey different valence and arousal levels associated with each of the two moods. In addition to recognition rates, they investigated how the robot's valence influenced the affect of the audience. They found that recognition rates for valence were quite low, as most participants assumed the robot was never in a negative mood. However, participant self-reports of valence and arousal were seen to align with those of the robot, indicating that the robot's mood condition directly influenced their own valence and arousal. These results indicate that mood/emotion contagion may be possible from a robot to people, regardless of whether they are able to directly recognize the robot's emotional display.

A similar study [49] investigated mood recognition and contagion of arm gestures during an imitation game with a NAO robot. Eight possible gestures were designed with the robot pointing its arms in different directions. The game was designed with either the gestures having positive or negative valence, and the imitation game sequence being easy or difficult. Participants were instructed to repeat the sequence of gestures demonstrated by the robot. Results showed that for both easy and difficult gesture sequences, participants
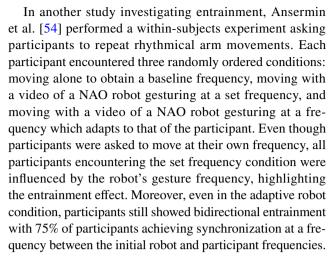
were able to recognize whether the gestures had positive or negative valence, and the reported affect of the participants themselves tended to align with gesture valence. Finally, participant game performance was consistently high for the easy condition, however, for the difficult condition, those observing gestures with negative valence outperformed those observing positive gestures.

Another study [50] explored the effect of specific gesture parameters used by a robot in expressing emotion. Participants designed waving and pointing behaviors for the NAO humanlike robot to align with negative, neutral, and positive valence by modulating a variety of parameters such as motion speed, decay speed, amplitude, repetition, and arm/finger extension. Though participant sample was too small to uncover significant findings, parameters corresponding to the different valence levels were consistent across participants. The waving behavior was also more easily and consistently designed than pointing, and certain parameters (such as amplitude, motion speed, and decay speed) seemed to be behavior-invariant.

English et al. [51] explored the concept of using robot gestures to teach children with Autism Spectrum Disorder (ASD) five of the six primary emotions (happiness, fear, sadness, anger, surprise). Using a NAO robot and a Mini Darwin humanoid robot, they programmed gestures for each of the emotions and conducted a pilot study to test the recognition of these emotions by adults without ASD to validate their development. Recognition rates were 100% for the Mini Darwin for all emotions except happiness (80%) and for the NAO robot were 96% for sadness, 78% for anger, 62% for both fear and surprise, and 57% for happiness.

2.1.3 Behavioral Response

In [52], Lorenz et al. investigated the movement synchronization of arm gestures between a human and human-sized mobile robot with two, seven degree-of-freedom (DoF) arms. The interaction scenario had the robot and a participant performing the repetitive task of moving a pen between two locations, where the two started either in-sync, a quarter-cycle off phase, or a half-cycle off phase. They hoped to observe whether humans would synchronize their movements to robots in various conditions when using a robot that would not adapt its own movements to the human (requiring the human to fully adapt to the robot). The in-sync start condition produced only a small amount of synchronicity in the task (15%), and the half-cycle (11%) and quarter-cycle (10%) showed even lower movement synchronization. This is interesting to note, as a previous study in [53], however, with two humans had shown that the two synchronized their movements over time when their movements had started out of phase.

In another study investigating entrainment, Ansermin et al. [54] performed a within-subjects experiment asking participants to repeat rhythmical arm movements. Each participant encountered three randomly ordered conditions: moving alone to obtain a baseline frequency, moving with a video of a NAO robot gesturing at a set frequency, and moving with a video of a NAO robot gesturing at a frequency which adapts to that of the participant. Even though participants were asked to move at their own frequency, all participants encountering the set frequency condition were influenced by the robot's gesture frequency, highlighting the entrainment effect. Moreover, even in the adaptive robot condition, participants still showed bidirectional entrainment with 75% of participants achieving synchronization at a frequency between the initial robot and participant frequencies.

Ende et al. [55] looked at recognition rates of a variety of different single arm gestures displayed by a human, humanoid robot (DLR mobile humanoid robot Justin), and industrial manipulator (DLR LWR III with a two-jaw gripper). They presented 20 different iconic gesture types and found that the gestures "stop", "From here, to there", and "This one" were the only three consistently identified by participants, regardless of arm type (identification rates of > 85%). Generally, across the 20 gestures, the human arm and humanoid arm had comparable average recognition rates (69% and 66%, respectively), however, the gestures displayed by the industrial manipulator were more difficult to identify (55% average recognition rate).

2.1.4 Task Performance

Regarding task performance, robot arm gestures have been shown to be influential in both improving the response time in interactive tasks as well as improving memory around storytelling.

Using a timed cooperation task, Riek et al. [56] investigated how people would interpret and respond to the three robot interactive arm gestures of beckoning, giving, and shaking hands displayed by the BERTI humanoid robot. The gestures were presented to participants either abruptly or smoothly and in a front-facing or side-facing orientation. They found that people had both the fastest reaction times and task completion times with abrupt gestures (over smooth ones) in a front-facing orientation.

Dijk et al. [57] used robot arm gestures to attempt to improve storytelling recall during HRI. The NAO humanoid robot was used to tell a story to participants with or without the use of iconic gestures (those indicative of actions in the story). When participants were asked to recall specific aspects of the story, it was found that gestures increased retention rates by approximately 10% overall and by over 15% for gestures associated with specific verbs and actions.

In [58], the communication effectiveness of different robotic arm and gripper poses are tested with participants in a collaborative human–robot assembly task. In an initial pilot study, participants were asked to generate appropriate arm gestures to instruct a human confederate on steps in the assembly task and in a subsequent study, these gestures were implemented on a 7-DoF Barret Whole Arm Manipulator (WAM) with a three-fingered BarretHand. Three conditions were used: two from different human-inspired gestures learned from the pilot study and one with a closed-hand configuration to act as a baseline. Looking at task recognition rates across directional, orientation, and manipulation commands, at least one of the three robot gestures were well recognized (> 60% rates) and recognition rates were typically higher with the two human-inspired gestures. However, three exceptions were found: (1) left and right directional gestures were confused with each other, possibly due to the angle of the arm relative to the assembly object, (2) the "swap" gesture—indicating an exchange of one part for another—was poorly recognized, possibly due to the complexity of the task, and (3) the "confirm" gesture—validating a successful assembly—was poorly recognized, likely due to the robot lacking a thumb and being unable to accurately replicate an appropriate human gesture.

Quintero et al. [59] investigated the effectiveness of a robot manipulator communicating through pointing gestures in a pick-and-place task. A 7-DoF Barrett WAM demonstrated four different gestures: standby, object pointing, yes, and no to show participants a series of pick-and-place actions. When compared to a human arm performing the same gestures, the robot arm was more poorly understood (28% misinterpretations vs. 10% for the human arm), however, was still understood better than chance.

2.1.5 Summary of Arm Gestures

Regarding cognitive framing, the use of robot arm gestures has been shown to improve participant evaluations on robot sympathy, liveliness, activity [40, 41], perceived anthropomorphism [42]. engagement [43], performance, and social ability [44]. Designing gestures in order to show high levels of competence and warmth for a robot can lead to perceptions of high affiliation with participants, however, also be perceived as being highly dominant [45].

With respect to emotive arm gestures, studies have shown that gestures using different motion parameters can successfully communicate both primary emotions (happy, sad, fear, anger, surprise) [51] and valence [49, 50]. However, even when an individual cannot recognize the emotion of a robot, robot gestures can emotionally affect individuals through emotion contagion [48].

For behavioral responses, robot arm gestures have been shown to be as successful as human gestures with communicating different commands, although humanoid arms tend to be more recognizable than industrial manipulators [55]. Robot arm gestures can also influence human behavior via entrainment, where a person's motion will adapt to match a robot's motion [54] much like humans do with each other [53]. However, synchronization can fail if the frequency of the robot arm gestures does not adapt to the human gesture frequency [52].

Robot gestures can also have a significant effect on human–robot cooperative task performance. Appropriate gestures have been shown to effectively communicate steps in an assembly task [58] and a pick-and-place task [59] as well as reduce both reaction time and task completion times [56]. During a storytelling scenario, a robot's use of coverbal gestures has also helped participants improve storytelling recall [57].

Generally, arm gestures can be an effective way for robots to influence people, potentially due to their larger movements and human tendency to prefer more dynamic, animated robot behaviors [43]. They are often combined with verbal utterances to enrich a statement [40–43, 48, 57] and, as will be discussed in Sect. 6, can often be used in multimodal nonverbal interactions.

2.2 Body and Head Movements

Body movements present full-body behaviors that can be both static (e.g. postures and poses) and dynamic. Body posture/pose has been shown to reveal the structure, content, and interrelationships of human interactions [60]. Head movements are associated with specific communication functions such as the overt semantic meanings of nodding and shaking for indicating referents during narration [61]. This section investigates how robot body and head movements during HRI influence cognitive framing of a robot, emotion recognition, and task performance.

2.2.1 Cognitive Framing

Robot body and head movements have been shown to influence human perception of a variety of different concepts including social engagement, intrigue, appeal, warmth, friendliness, empathy, and enjoyment.

Investigating a robot as a peripheral companion, Hoffman et al. [62] had the Kip1, a small lamp-like robot, display postures in response to a human–human conversation. As two people conversed, the robot varied its posture between neutral (during no conversation), calm (at the start of a conversation), curious (after ongoing conversation), and scared (during loud conversation). These postures were found to make Kip1 be perceived as socially engaging with an intriguing, social-emotional appeal, but without distracting from the core human–human conversation.

Compared to the neutral body language condition, when Kip1 displayed calm, curious, and scared postures, it was also identified to be more warm, friendly, social, and empathetic, indicating that people related to it not simply as an object, but potentially as an emotion-forming entity.

In [63], the effects of humanlike body movements and robot-specific behaviors were investigated with the NAO humanlike robot during storytelling. Participants would be told a story by the NAO robot in one of three conditions after which the robot would ask the participant to tell their own story. A control condition with audio only was compared to humanlike body movements (dancing, nodding to music, etc.) and robot-specific behaviors (LED coloring) to see how they would each influence perceptions of the robot on anthropomorphism, animacy, likeability, and intelligence. Both behavior conditions were rated higher on all metrics than the motionless control, the humanlike body movements were rated the highest, even above a forth condition that combined both humanlike and robot-specific behaviors. Though the researchers acknowledge the value of robot-specific cues in some situations, their findings generally showed a human preference for humanlike behaviors.

Choi et al. [64] used mimicry to investigate the influence of body movements on a person's framing of similarity and closeness. The experiment was unique as it used a telepresence robot with a human operator displayed on the screen but with the experimenters controlling the robot's movement while interacting with participants. The participant and the operator engaged in a "get-to-know-you" exercise while the robot was controlled under one of three conditions: mimicking the partner's body movements and orientations, random movements, or stationary. The results of a post-trial survey showed that participants felt the highest similarity to the operator in the mimicry condition, followed by the random and then stationary conditions. Though measures of closeness showed no significant results across the whole population, a gender effect was seen whereby women felt highest closeness to operator in the static condition, followed by the random and then the mimicry conditions, while men reported the exact opposite; feeling highest closeness with the mimicry condition.

To better understand the effects of robot head movements on enjoyment, Wang et al. [65] invited participants to play with the human-like robot Nico in an open-ended manner. Nico interacted with them using four head-tracking modes: no tracking (static head), smooth movement tracking, fast tracking, and participant avoidance (looking away). Results showed that participants rated the highest enjoyment levels for the avoidance and fast-tracking modes, particularly those participants who did not have any prior robot experience. This finding was different than their hypothesis of preference for smooth tracking based on typical human–human

behavior, indicating that human–human realism may not always be the expected behavior during HRI.

2.2.2 Emotion Recognition and Response

Head and body movements have been tested in several different emotion recognition scenarios where both specific emotions—sadness, joy, anger, fear, surprise, disgust, happiness, curiosity, disappointment, and embarrassment—as well as more general rankings of valence and arousal have been explored.

McColl and Nejat [66] explored the recognition of emotive robot body movements and postures using the humanlike robot Brian 2.0. The robot displayed different human body language defined by Wallbott [67] and de Meijer [68]. For their study, participants were asked to identify the emotions of sadness, joy, anger, interest, fear, surprise, boredom, and happiness displayed by both the robot and a human actor. Comparable recognition rates were obtained for the emotions of joy, surprise, and interest, while a higher recognition rate was obtained for the robot for the emotion of sadness. The latter could be potentially due to the robot's greater downward movement of the head during this display (i.e. exaggerated movement).

Embgen et al. [69] investigated emotion recognition of robot head movements by creating head movement sequences derived from the analysis of head movements typically displayed by humans and animals. Using Daryl, the human-like robot, they designed movements for the emotions of anger, disgust, fear, happiness, curiosity, disappointment, embarrassment, sadness, and surprise. The head movements were augmented with an LED-lit chest that could change color to indicate different emotional intent. They found that users were able to recognize all intended emotions better than chance, and at high rates for curiosity, happiness, and fear. However, they did not differentiate between the effects of head movements and the LED display.

Saerbeck and Bartneck [70] investigated arousal and valence recognition when varying the acceleration and movement curvature of the head of an iCat cat-like robot. They chose these two movement parameters as they had been shown in [71] to be the most influential towards perceived animacy and emotional expression. iCat performed a simple task of moving its head between two different objects using varying combinations of low, medium, and high acceleration and curvature. Participants were then asked about their perceptions of the robot's arousal and valence with respect to the movements. Their findings showed that acceleration was correlated with perceived arousal, however, valence was not correlated to either acceleration or movement curvature. Moreover, all participants were surprise following the experiments by the variety of emotions the robot was able to accurately convey.

Beck et al. [72] used the NAO robot to investigate if it was possible for people to interpret robot emotions displayed through body poses and head positioning that lacked facial expressions. Though they found that head positions had the highest effect on the recognition rate, they also demonstrated that humans can identify emotions (angry, sad, fear, pride, happy, excited) through robot postures better than chance. The authors repeated these experiments with children [73, 74] to observe the differences between adult and child perceptions of the robot. Children were able to recognize emotional intent with better-than-chance recognition rates; however, it was seen that the children were somewhat less successful than adults at interpreting emotion displayed through body postures. In another study presented in [75] using a similar experimental setup, the same authors found that adult participants were even able to recognize postures generated algorithmically by blending (interpolating positions) between two different emotional poses (i.e. 70% sadness and 30% fear).

2.2.3 Task Performance

Moshkina [76] investigated the effects of robot postures on compliance speed and effectiveness in emergency situations, i.e., evacuation. They had a NAO robot display negative mood through keeping its head down and periodically looking side to side, as though to check for danger while also expressing fear periodically by crouching low with its head down, covered by its hand. Evacuation commands were issued to human participants with three conditions: control (no expressions), negative mood (only the mood pose described), or both (periodic inclusion of fear to negative mood). The results found a similar decrease in participant compliance time and increase in evacuation distance for the 'negative mood' and 'both' conditions compared to the control condition. Presumably, this result is because the display of the robot's negative body postures was also found to cause increased levels of nervousness in the participants, indicating an effective emotion contagion.

In [77], body movements were used as warning signals in human–robot tasks to indicate confidence levels of the robot to the human. In the experiment, a NAO robot asked participants to pick a brick from a cup full of Lego bricks, however, would periodically knock the cup off the table, and participants would have to clean up the bricks before proceeding. Two conditions were used with this experiment: a control that made mistakes without warning and one where the robot's mistake was preempted by its body movements indicating uncertainty in the task. Unsurprisingly, the uncertainty condition led to participants taking more preventative actions such as making a barrier or deliberate movements to catch the cup. In addition to improving scores of robot trustworthiness, understandability, and reliability, the uncertainty

condition also led to tasks with significantly fewer errors and faster completion time.

2.2.4 Summary of Body and Head Movements

The use of robot body and head movements can influence the cognitive framing of robots across a number of different social metrics such as social engagement, intrigue, and social appeal [62], anthropomorphism, animacy, likeability, intelligence [63], and enjoyment [65]. Even with telepresence robots, cognitive framing can be influenced on similarity and closeness with respect to the person operating the robot [64].

Moreover, emotional displays through head and body movements tend to be recognizable by humans better than chance for specific emotions [66, 69, 72, 73] as well as for more general scales of valence and arousal [70]. This recognition success can even be extended to displays of algorithmically blended emotions created by interpolating between two unique sets of nonverbal behaviors [75]. In some cases, the use of this modality can lead to emotion contagion [76], causing a human to be nervous after a robot's display of fear and negative mood [77].

2.3 Eye Gaze

Eye gaze in human to human interaction is a behavior often used to convey interpersonal intent, exert dominance, socially bond, and even manipulate another person's physiology [78, 79]. A robot's use of appropriate eye gaze has the potential to support or accomplish numerous objectives in social interactions with humans. The papers surveyed herein explore how robot gaze influences human task performance within several different activities.

2.3.1 Task Performance

The impact of eye gaze on human performance has been explored across a variety of task types such as simple teaching tasks, map drawing tasks, guessing games, and object handover tasks. Task performance itself was been considered with respect to completion time, reaction time, and error rates.

Breazeal et al. [80] created an interaction between the furry Leonardo (Leo) robot and a user engaged in a simple task in order to investigate how robot gaze affects task performance. Participants were asked to each teach Leo the locations of three buttons, verify that Leo knew the locations, instruct Leo to turn the buttons on, and confirm task completion. This sequence was performed with both the presence and absence of Leo's gaze watching the participant and buttons, while measuring task completion time and errors. In the eye-gaze present condition, time

to complete the task was reduced by 43% on average and the number of errors were cut in half when compared to the absent condition. Questionnaire results showed that participants also perceived Leo as more understandable, and that they were able to build a clearer mental model of the robot when it used eye gaze.

Skantze et al. [81] also investigated gaze and task performance for a map drawing task. The Furhat robot head was used to guide participants in drawing a map. The robot head augmented its verbal instructions with three different gaze conditions: gaze absent (covered robot face), consistent gaze at the relevant map location, and random gaze behavior at the user and non-relevant map locations. Participants completed the task faster and identified the robot as more helpful in the consistent gaze condition versus the absent or random gazes. The random condition was found to confuse participants and as such, had the slowest task completion times.

Stanton and Stevens [82] also explored how robot gaze influences humans in task completion, in particular looking at decision-making scenarios. Participants played a visual identification "shell game" of increasing difficulty (where they must find a marker hidden beneath one of three moving shells) with a NAO robot acting as a helpful team member. Experimental conditions that were tested with the robot consisted of maintaining gaze at the game or looking at the participant during the answer period. They found that the robot's gaze towards the participant had a positive effect on trust for the difficult game scenarios when the user required more help from the robot, but a negative impact on trust for easier scenarios. This, coupled with participants responding faster when the robot gazed at them, led the authors to postulate that robot gaze was introducing a sort of "social pressure" on the participants.

Lastly, Moon et al. [83] conducted experiments to investigate the effects of gaze cues on human-to-robot object handover tasks. With a PR2 robot, they created three gaze conditions: no gaze (looking away), gaze at the shared handover location, and alternating gaze between handover and the participant's face. They recorded influence on both handover time and participant preference of the three states. While both gaze conditions improved the handover time over the no gaze condition, gaze at the shared handover location led to the fastest time. However, participants reported that they preferred the alternating gaze condition the most as the robot made eye contact with them. Zheng et al. [84] extended this experiment further and, in addition to confirming the handover time improvements through the use of gaze, also found that the use of robot gaze influenced the participant's gaze direction to be towards the handover location. This potentially explains the increased handover speed as the participant's gaze was focused on the handover location and presumably, the task at hand.

2.3.2 Summary of Eye Gaze

The presence of task-appropriate robot gaze can lead to user performance improvements across several different tasks [80–84]. Robot gaze behaviors have been shown to contribute positively robot understandability and lead to reductions in task completion time and errors [80]. Another study showed coverbal gaze instruction to improve robot helpfulness and lead to reductions in task completion time [81]. Gaze has been shown to be an effective primer in handover tasks, influencing users to match the robot's gaze [84] and reducing completion time [83]. In difficult tasks involving human uncertainty, robot gaze was found to have a positive influence on trust in the robot as a collaborator [82]. However, caution will need to be taken when designing robot gaze behaviors as they could have the potential to introduce negative influences such as social pressure [82].

2.4 Facial Expressions

There is a well-explored theory that facial expressions evolved from ancestral reflexes and are therefore universally understood in human interactions [85]. Research has also shown high effectiveness of the face in communicating emotional intent [86] and affect [87] among people. This universality and efficacy of communication motivates the exploration of how robotic facial expressions influence humans. Herein, how robot facial expressions influence people will be investigated with respect to cognitive framing, emotion recognition and response, behavioral response, and task performance.

2.4.1 Cognitive Framing

Facial expression research has investigated ways in which a robot's face can influence numerous concepts such as empathy, likeability, perceived intelligence, acceptance, perceived enjoyment, friendship, companionship, alliance, happiness, deception, and contextual fit.

To explore how facial expressions influence the perception of a robot, Gonsior et al. [88] developed the EDDIE robot head to play a guessing game with participants, attempting to determine which fictional character the participants were pretending to be. The robot generated facial expressions that were a combination of anthropomorphic and zoomorphic facial features and were displayed under three conditions: neutral (no facial expressions); mirroring participant facial expressions; and socially motivated expressions developed in reaction to the participant's facial expressions. Results showed that for both the mirroring and social motivation conditions, participants rated user acceptance, likeability, and perceived intelligence significantly higher than the neutral condition. In particular, perception of the

robot on sub-concepts of empathy, subjective performance, and perceived enjoyment showed an almost 50% improvement in scores between the neutral and social motivation conditions. However, regarding perceived safety, the introduction of facial expressions actually lowered participant scores.

Leite et al. [89] investigated human perception of facial expressions with the iCat robot watching and reacting to two participants playing a chess game. The robot was assigned to be aligned with one player while opposing the other. After each chess move, the robot would attempt to display empathy through verbal utterances and facial expressions in support of one player while showing opposition towards the other. These were either in the form of "rewards" or "punishment" and each varied along a scale of weaker, expected, stronger, and unexpected. Those who received supportive comments and facial expressions rated the robot higher on friendship, companionship, alliance, and self-validation (participant reassurance), while those receiving opposing behaviors scored each of these significantly lower, however, in interviews mentioned that they still valued the robot's feedback.

Endrass et al. [90] explored the use of facial expressions in lying and deception by trying to show different types of happiness (those indicative of deception) with the Alice doll-like robot. Alice was programmed with seven different smile types including with or without squinting eyes, three intensities of asymmetric mouth, blended with anger, and blended with surprise. All but one (smile without squinting eyes) were hypothesized to be "deceptive" smiles, indicative of human lying and anticipated to have lower happiness scores. Participants were asked to watch videos of Alice's different smiles and comment on Alice's perceived happiness. Compared to the smile without squinting eyes, a reduction in happiness (hypothesized to be aligned with deceptive smiles) was perceived with smiles that involved changes of the mouth, however, not with smiles that only involved changes with the eyes. This finding indicated that, at least for determining the robot's happiness levels, participants focused more on the mouth region than the eyes.

Hegel et al. [91] used the anthropomorphic robot BARTHOC Jr, to investigate a robot's ability to recognize human emotion and react appropriately to it. Participants were asked to read a short children's story, and, at each section, the robot would use the participant's vocal intonation to determine the emotional content of the situation. The robot would either respond with facial expressions (happy, fear, anger, disgust, surprise, sad) or use a simple nod to acknowledge the end of a section. Participants generally perceived the expressive robot as having both greater "emotional recognition" and "situational fit" with the story, particularly in sections of the story associated with sadness.

2.4.2 Emotion Recognition and Response

With regards to human recognition of robot emotions, several studies have been performed where participants were asked to identify facial expressions associated with the six primary emotions of happiness, sadness, anger, fear, disgust, and surprise.

Berns and Hirth [92] investigated the recognizability of emotions via facial expressions using the expressive robot head, ROMAN. They created facial displays for the six primary emotions using a combination of arousal, valence, and stance. These robot expressions were presented to participants through pictures and a video, and they were asked to identify the intended emotion of the robot. The medium of presentation did not affect the identification rates and it was found that the participants were able to recognize anger, happiness, sadness, and surprise better than chance, however, were not able to do so with fear or disgust.

Kobayashi et al. [93] developed a human-like robotic face, Face Robot Mk II, that used electrical shape memory alloy actuators to display a variety of facial expressions to be recognized. Through actuation of the lips, nose, cheeks, brow, and chin, they created expressions for the six primary emotions. They showed images and a video of the robot expressing these emotions to participants and asked them to identify each. Results were again similar for both image and video format, and showed 100% recognition for happiness and sadness, > 90% recognition for anger and disgust, and > 80% recognition for surprise and fear.

Allison et al. [94] tested emotion recognition with the human-like Brian robot, that generated facial expressions using a unique muscle-based facial actuation system. Participants were shown the robot in-person and asked to identify the emotional intent behind its different facial expressions while it was displaying all six primary emotions. In preliminary experiments, they were able to show that a group of participants had a 100% recognition rate for the emotions of happy, sad, surprise, and fear, and 80% for angry and disgust.

In [95], Cameron et al. studied the influence of life-like affective facial expressions on children's emotional behavior with the Zeno R50 humanoid robot. They presented Zeno to children during a brief game-playing interaction and recorded their proximity to the robot, facial expressions, and speech. Two conditions of Zeno were presented to either interact with or without the use of contextually appropriate positive and negative facial expressions at different points in the game. Their findings showed that male participants showed a positive affective response and indicated greater liking towards the robot in the facially expressive condition. However, female participants showed no significant difference between the two conditions.
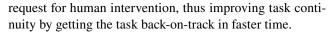
2.4.3 Behavioral Response

When investigating engagement, Gordon and Breazeal [96] used the toy-like robot DragonBot to test and optimize the facial expressions that would sustain human engagement. The experiment was conducted in a large, crowded festival environment, and the robot was tasked with the goal of keeping as many people as possible in its close field of view for as long as possible. They programmed nine different facial expressions (associated with concepts like 'Yes', 'I Like It', 'Sad', 'Shy', and 'Think') for the robot to optimize, and after only 2 h of interactions, the robot was able to identify that the 'Sad' expression was the best for keeping users engaged. On average, people would stay with the robot for 30 s following a 'Sad' expression, compared to < 15 s for most others. The authors hypothesized that the robot's "infant-like face with big sad eyes" in the 'Sad' expression was able to influence human behavior based on findings from prior research that showed human preference towards animals who exhibited more child-like facial expressions [97].

In Chevalier et al. [98] the Zeno small humanlike robot was designed to facilitate a game with children, where the two take turns mimicking each other's facial expressions. A usability study with children was conducted. Even though the study only had a small number of participants, it was observed that the children were engaged in interacting with Zeno and willing to play the imitation game, while frequently attempting to mimic the robot's facial expressions.

Another study [99] looked at imitation and mimicry with autistic children and Mina, a young-looking humanlike robot. Mina was developed to recognize and mimic facial expressions with a fuzzy finite state machine which classifies facial expressions into one of eight possible facial expressions. A pilot study introduced Mina to autistic children, ages 3 to 7 years old, and found that, when asked to interact in an imitation scenario, 78% of participants engaged with and mimicked the robot.

2.4.4 Task Performance

Reyes et al. [100] explored the impact of negative robot facial expressions on collaborative task performance. Using the Golem-III human-like robot, a simple human–robot collaboration task was created, where the robot and a participant needed to place ten objects in a container. The robot was designed to fail for some of the tasks. The experiments consisted of the robot either displaying a neutral face, or happiness when succeeding, and sadness if there was a failure in the task. During the task, it was observed how robot displays of sadness during failures would affect performance recovery. They found the robot's negative feedback during failures helped to regulate the task by communicating a request for human intervention, thus improving task continuity by getting the task back-on-track in faster time.

In [101], the BERT2 upper-torso humanoid robot was used to provide facial expression feedback around mistakes in a collaborative omelet cooking task. In this within-subjects study, participants were instructed to cook an omelet with all of three robot conditions: non-communicative and most efficient, non-communicative but makes mistakes, or facially expressive and makes mistakes. Although the first condition had the fewest mistakes and the fastest task completion time, the expressive condition had the highest satisfaction ratings by the participants and rated the lowest on frustration and temporal demand. This suggests that in human–robot task collaboration, efficiency may not always be the most important consideration for users.

Another study by Cohen et al. [102] investigated the use of positive facial expressions on a robot during a cooperative, human–robot task. Trials were conducted using individuals with schizophrenia as well as a control group without schizophrenia. Using the iCub childlike robot, participants performed a simple mirroring task of following the robot's hand motion as closely as possible. As the participant achieved greater synchrony, the robot provided positive feedback through one of three conditions: vocal only, vocal with a mounted tablet displaying a "+" sign, or vocal with the robot displaying a smiling face. Findings showed that, compared to the vocal only and "+" conditions, the smiling face condition had a faciliatory effect on synchrony for the control group but not for the schizophrenic population.

2.4.5 Summary of Facial Expressions

Robot facial expressions can influence user cognitive framing on a number of concepts such as acceptance, likeability, perceived intelligence [88], friendship, companionship, alliance, self-validation [89], emotion recognition, and situational fit [91]. Different types of robot smiles can also be interpreted by people as a robot's varying levels of happiness, and sometimes indicate a robot lying or being deceptive [90].

Emotions have been shown to be successfully recognized by participants when using robot facial expressions, particularly the six primary emotions of happy, sad, angry, fear, disgust, and surprise [92–94]. They can also be used to effectively communicate positive or negative valence [95].

Regarding behavioral responses, robot facial expressions can encourage engagement with and mimicry of a robot by normally-developing children [98] and those with autism [99]. Specific facial expressions, such as sadness, can increase user engagement with a robot [96], likely due to large-eyed, paedomorphic features [97].

In task-based scenarios, robot facial expressions have been shown to quickly communicate failure and the need

for help, improving completion time [100]. In some cases, an expressive robot that provides facial expression feedback around failures is even preferred to a non-expressive robot that operates flawlessly [101]. However, caution should be taken with using facial expressions in all situations as some have also been shown to lower perceived safety [88], potentially due to the more dynamic nature of the robot.

3 Proxemics

Proxemics pertains to the perception and use of space as it relates to communication, namely, the conscious or unconscious setting of distances between various objects, agents, and oneself [103]. Social distances or "personal space" in human interactions have been categorized by Hall [23] into four proxemic zones: public (< 12 ft); social (4–12 ft); personal (1.5–4 ft); and intimate (0–1.5 ft). These zones are relevant for communicating specific meaning between two individuals in both *social distance* and *social transit*, which will be discussed in this section to determine how proxemic nonverbal communication affects human performance and cognitive framing of a robot.

3.1 Social Distance

Social distance and orientation between people can contribute to comfort levels, affiliation, and intimacy [104], as well as more functional outcomes such as listening comprehension [105]. In the robotics community, the proxemic framework established by Hall [23] is typically used to investigate approach distance—the distance a human stops or requests for a robot to stop from each other. This section will investigate how this distance influences humans' cognitive framing of robots and outcomes in task performance.

3.1.1 Cognitive Framing

Variables such as comfort level, competence, anthropomorphism, engagement, and likeability have all been explored as cognitive frames influenced by proxemic distance in HRI as will be discussed below.

In [106], Walters et al. explored comfortable approach distances from both a robot approach perspective and a human approach perspective using the PeopleBot telepresence robot. They found that the majority of participants (60%) were comfortable approaching or being approached up to a social distance of 4–12 ft, which is compatible with human–human interaction distances, however, a large minority (40%) actually approached the robot up to a distance that would be synonymous with intimate or

threatening behavior, i.e., < 1.5 ft. They also found that human personality traits such as timidity and nervousness increased comfortable approach distance whereas traits like proactiveness decreased comfortable approach distance. In subsequent work presented in [107], Walters et al. performed long-term studies with the PeopleBot robot to investigate changing proxemic effects over time using an Autonomous Proxemic System that measured human–robot proxemics and controlled approach distance. As participants in a simulated household environment interacted with the robot over a 5-week period and became more experienced with the robot, they decreased their social distance to the robot and became more comfortable with the robot. However, this change typically happened within the first 2 weeks, after which their approach remained relatively consistent at the aforementioned social distances for the remainder of the 5 weeks.

To investigate perceived safety levels associated with distance and velocity, Shi et al. [108] used a Segway robotic platform to approach participants under different motion conditions. Participants stood still while the robot approached them at either a slow or fast velocity (2.0 m/s or 4.5 m/s) and to a distance of either 0.5 m (intimate) or 1 m (personal). Participants were asked whether they felt safe, slightly unsafe, unsafe, or very unsafe. The distance itself did not affect the participants, however, for the fast velocity condition, participants' average response was that they felt slightly unsafe and some participants even moved away from the robot's path as it approached them.

In [109, 110], Mead and Mataric explored the impact of robot task performance on frames of the robot's competence, anthropomorphism, engagement, and likeability. Using either voice or pointing gestures, participants commanded the "Bandit" human-like robot to look at different objects in the room. The robot would then indicate whether it understood the command. For each scenario, the robot's performance was artificially attenuated by introducing intentional errors correlated to the distance of the robot from the person. This distance was varied between trials to provide a distribution of errors determined by the minimum and maximum probability of robot recognition. The aggregate of these trials dictated a minimum and maximum performance level (which also resulted in an average performance level). Robot competence, anthropomorphism, and engagement were all found to be correlated to the minimum and average performance levels, however *not* correlated to the maximum performance level. Likeability was significantly correlated to all three levels (min, max, avg.). This suggests that, influence on human framing of robot competence, anthropomorphism, and engagement, should focus on average robot performance across many interactions as opposed to maximum performance across a few interactions.
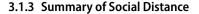
3.1.2 Task Performance

The influence of social distance on task performance was investigated in [111] by Koay et al. for performing a basic object handover task with a seated participant. The Care-O-bot robot approached a participant and stopped to deliver an object at four distinct positions with respect to the participant: front or side close (0.5 m—intimate), or front or side far (1 m—social). Their findings showed participants preferred to be approached from the front versus the side, however, more significantly at a close distance versus far, largely due to a justification of practicality. In particular, the closer distance may have been preferred due to considerations of arm length or dexterity in object handoff from the robot.

Kim and Mutlu [112] investigated the effect of social distance and role on task performance and participant enjoyment in two different tasks using the Wakamaru robot. In the first study, participants were to collaborate on a memory game with a robot taking a subordinate or superior role at either a close (46 cm) or distant (120 cm) proxemic distance. In the second study, participants played a game of chess either collaborating or competing with a robot again at either the close or distant proxemic distance. Task performance was reported as a more positive experience by participants when the robot was close in the supervisor and competitor roles, and when the robot was distant in the subordinate and collaborator roles.

Papadopoulos et al. [113] investigated the effects of proxemic position on engagement and collaboration in a memory task. The upper-torso of a NAO robot was positioned at a table and provided support to participants in a memory game. The robot was programmed to have either helpful or neutral speech behavior and was either placed in a frontal or lateral position relative to the participant. Their results showed that participants were more engaged and had higher preferences for the robot in the frontal versus lateral position, and the helpful versus neutral behavior.

In [114], the effects of social distance were tested on the performance of a human's willingness to donate money to the Mobile Dexterous Social (MDS) humanoid-torso robot. The MDS robot attempted to solicit donations from participants at either a 'close' (2.5 ft) or 'normal' (5 ft) distance. Though distance alone was not found to have any significant influence on donation size, they did find that male participants gave more in the 'close' condition versus the 'normal' condition, while female participants gave more in the 'normal' condition compared to the 'close' condition. It is worth noting that the MDS robot presented itself as female for these trials.

3.1.3 Summary of Social Distance

In general, comfortable approach distances between humans and robots are similar to those seen in human-to-human interactions [106, 111], though many individuals approached robots closer than a typical human to human approach, inside of the 'intimate space' [106]. Long-term studies [107] showed reductions in comfortable robot approach distance over time, however, a steady state was reached after only a few interactions. It is unclear if this effect was due to the participants becoming more comfortable with robots in general or to the specific robots they interacted with.

With respect to both distance and velocity, velocity was shown to have a greater influence on perceived safety, with higher velocities making participants feel unsafe, whereas distance did not have an influence on safety [108].

Robot task completion played an important role in determining appropriate approach distances and directions to ensure the robot could function correctly [111]. Furthermore, different tasks and social roles seem to dictate user preferences for a robot's proxemic distancing. In game tasks, robots in supervisor and competitor roles should be closer to the user, while robots in subordinate or cooperator roles should have more distance [112]. Users also prefer robots in a frontal versus lateral position when collaborating on memory tasks. Finally, regarding donation solicitation, men were more willing to give more money when a robot asked at a 'close' distance whereas women were more willing to give to a robot at a 'normal' social distance [114].

3.2 Social Transit

Transit behaviors such as passing and following are important to consider, to maximize safety and comfort when people are sharing environments with moving robots [30]. This section investigates how different factors such as distance, speed, stopping, and path can influence a person's cognitive framing of a robot as it is traveling near a person.

3.2.1 Cognitive Framing

The cognitive frames of comfort, politeness, trust, naturalness, and human-likeness are explored herein in different scenarios where robots are passing, approaching, and following people.

Pacchierotti et al. [115] investigated a person's comfort with respect to the PeopleBot passing him/her in a confined space such as a hallway. A person and robot were placed on a collision trajectory and then the lateral distance between the two was introduced in three conditions—0.2 m, 0.3 m, and 0.4 m (all within an intimate zone)—as the robot changed its course and passed the person. Participants stated that they were uncomfortable with the robot entering their intimate

space during passing and understandably were more uncomfortable for closer passing distances. However, when a second set of trials was conducted with the same participants, comfort levels for all distances increased, indicating a growing trust. Even though participants were uncomfortable with the robot entering their intimate space, when asked, they also felt it was unnecessary to take more significant avoidance actions than were used by the robot.

In another exploration of comfort in proxemic interactions, Butler and Agah [116] ran experiments with a Nomadic Scout II small cylinder robot. Participants interacted with the robot in an approach scenario and a passing scenario. The approach scenario had three conditions of either slowing the robot's velocity, increasing its velocity, or turning slightly. The passing scenario occurred when the robot came near the participant and it would choose to either stop and adjust course before continuing or make subtle adjustments to avoid the participant while moving. In the approach scenario, participants were least comfortable with the velocity increase but had similar responses to the slow and turn conditions. In the passing scenario, participants were more comfortable with the adjustment condition over the stopping condition. While not explored further in the paper, the stop behavior seemed to lower comfort levels, potentially due to the communication of something bad that warranted stopping.

Tsui et al. [117] explored robot passing behaviors with respect to politeness and trust of the robot. They used different robots in the trials: a small mobile Kyosho Blizzard, a larger mobile ATRV-Jr, and a robotic powered wheelchair with a rider present. Four passing behaviors were considered: stopping, slowing down, maintaining velocity, or speeding up. Participants watched videos of the different robots and behaviors. With regards to robot type, participants trusted the wheelchair the most, however, the Blizzard robot was perceived as behaving the most appropriate. Regarding passing behaviors, participants stated that the most polite and trustworthy behavior was the stopping, followed closely by the slowing down. The authors believed that this was due to the increased reaction times afforded by these behaviors in case of unexpected behavior. That said, when questioned about how they believed the robot should behave, participants responded that a robot should move in the same way as humans: constant speed for passing unless there is a reason to slow or stop.

To investigate natural and human-like behavior of robots during following, Gockley et al. [118] used the Grace cylindrical mobile robot to follow participants using two different methods. In the direction-following method, the robot attempted to drive towards the current location of the person whom it was following, whereas, in the path-following method, the robot tried to follow the original path of the person as closely as possible. It was observed that all participants generally considered the direction following approach more natural and human-like.

3.2.2 Summary of Social Transit

Social transit research has shown that users can be uncomfortable with robot passing behaviors that enter their intimate space [115], however, they became more comfortable with repeated interactions [115]. Higher velocities can understandably lead to higher levels of discomfort [116], however, unexpectedly, stopping during passing was found to have conflicting findings. One study found that a robot stop behavior during passing led to human perceptions of politeness and trustworthiness [117], although in the same study participants stated that they expected robots to navigate and pass them in the same manner as a person would (without stopping). In another study, stopping during passing actually lowered comfort levels, potentially because it signaled something was wrong [116].

In scenarios where a robot is following a person, the more natural and human-like approach is for the robot to drive towards the person's current location, rather than exactly follow their previous path [118].

4 Haptics

Haptics was long considered to be intrinsically tied to proxemics [119], however, it began to have its own importance as the "earliest and most elemental mode of communication" that deals with how touch communicates signals from the outside world to people through the skin [24]. In 1965, Austin coined the term Haptic Communication as the study of patterns of communication with respect to tactile interactions [120]. Haptic communication in HRI is still an emerging field, where safe robot tactile behaviors such as hand shaking, and gentle touching have been investigated, and specifically how these types of interactions influence people. Herein, we examine how robot touch plays a role in cognitive framing, emotional recognition, and task performance.

4.1 Cognitive Framing

The influence of robot touch has been investigated with respect to enjoyability, necessity, human or machine-likeness, and dependability, as identified in the papers described below.

To investigate the influence of robot touch in a care environment, Chen et al. [121] had participants lay in a simulated hospital bed where Cody, the mobile manipulator robot, would interact with them. Though their experimental procedure kept the robot motion and touch gesture consistent throughout all interactions, the robot would implement

the touch either with or without a verbal warning, or an explanation of why the robot was touching the participant, namely, whether the touch was functional or affective. Participants found that the enjoyability and deemed necessity of the touch were both higher when accompanied with a functional explanation compared to an affective explanation, though for both explanations, participants responded that they would allow the robot to touch them again. Surprisingly, when comparing a warning versus no warning before the touch, participants were more favorable of touch without a verbal warning. This highlights the importance of how a behavior is contextually framed, in this case with respect to warning and explanation.

Robot touch was also investigated by Cramer et al. in [122]. Videos of the humanoid Robosapien helping a user having computer problems were shown to participants. Four different interaction conditions were shown, where the robot talked through the problem with the user by varying both its touch (present or absent) and proactiveness (offer help or wait to be asked). The participants ranked the robot with respect to human-likeness, machine-likeness, and dependability. The results showed that the proactive robot was identified as less machine-like when touch complemented its behaviors. The reactive robot, on the other hand, was identified as less dependable when its behavior also involved touch. Participants who had a positive attitude towards robots, also perceived the robot as more human-like when it touched the user. These experiments show that while touch can be effective in perceiving robots as more human-like, the overall robot behavior and general attitudes towards robots of the users need to also be considered.

Fukuda et al. [123] explored the effect of touch in an ultimatum game to see how a robot touching a person would influence their feelings about the robot. Using a Robovie-mR2 upper-torso humanoid robot, participants were offered unfair proposals with one of two potential conditions: a touch condition, where the robot touched the participant's arm, or a no touch condition. Measuring Medial Frontal Negativity (MFN) through EEG, results showed that the no touch condition led to higher MFN amplitudes, suggesting that a robot's touch may inhibit the negativity and sense of unfairness experienced by participants towards a robot acting unfairly.

The enjoyment and happiness of individuals receiving a head massage was explored by Walker and Bartneck in [124]. Observing participant facial expressions and issuing participant surveys on enjoyment, a within-subjects experiment exposed participants to three conditions: participants massaging their own head (self), participants receiving a massage from another person (human), and participants receiving a massage from a NAO humanoid robot (robot). The mean rating of pleasure (out of 5) on a Likert survey was highest for the human condition (4.1), over the self (3.7)

and robot (3.5) conditions. However, a video analysis counting participant facial expressions showed that expressions of happiness were highest for the robot condition (average 3.5 per participant) over the human (2.3) and self (1.1) conditions.

Willemse et al. [125] investigated whether robot-initiated social touch could induce people physiologically, perceptually, and behaviorally. Participants were invited to watch a scary movie with a robot that spoke soothing words to them in the control condition and, in the touch condition, the words were accompanied by a touch on the shoulder. Though they measured and hypothesized participant changes in physiological (heartrate, galvanic skin response, respiration), perceptual (attitude towards robot, social relationship, robot appearance), and behavioral (willingness to donate), no significant differences were seen between the touch and control conditions.

4.2 Emotional Recognition and Response

Yohanan and MacLean [126] developed a robotic, pet-like "Haptic Creature" with the ability to create haptic affective expressions when being held by a user. While touching the robot, it could simulate haptic effects of breathing movement, purring vibration, warmth, and varying ear stiffness. Wearing earmuffs to block out any sounds from the robot, participants had the robot placed in their laps whereupon it would present one of nine haptic behaviors aligning to the nine "key expressions" (e.g. excited, distressed, relaxed, and depressed) defined along the arousal and valence dimensions of the circumplex model [127]. Participants had to determine both the robot's intended key expression (provided to them in a list) as well as indicate the arousal and valence levels of the robot. Results showed that they were able to correctly recognize between 17 and 52% of the nine possible expressions, having greater success with "distressed" and "pleased." Participants were also successful at identifying the arousal levels of the key expressions. However, participant categorization of valence into negative, neutral, or positive was generally unsuccessful. In a similar study presented in [128], the authors tested breathing more explicitly and found that the robot's breathing motion was noticed by participants, however, the affective intent (arousal and valence) of the breathing was not generally understood.

The calming effects of the aforementioned "Haptic Creature" were investigated in [129]. Participants held the robot in their laps and were instructed to stoke the robot while the robot was either inactive or providing simulated breathing through vibratory haptic feedback. The results showed that heart and respiration rates—metrics for calmness—significantly decreased for the participants with the breathing robot compared to the non-breathing robot.

Another study [130] investigated the recognizability of emotional arousal by varying the breathing speed of a robot using vibration. A small, stuffed toy bear robot was used with vibration motors and a small air bladder which simulated the effects of breathing over six different speeds from none (0 per minute) to very fast (56–60 per minute). Participants were asked about the robot's conveyance of the emotions "lively" and "pleasant", and it was found that higher speeds of breathing corelated to a higher "lively" rating, however, "pleasant" did not correlate to breathing speed. A later study [131] with the same robot investigated how participants perceived the "pleasantness" and "stimulation" of a photo while holding the breathing robot. They found that while different conditions of robot breathing did not influence "pleasantness", they were more stimulated by the photographs when the robot was breathing versus not breathing. They were also more stimulated by a fast-breathing robot when viewing "high arousal – pleasure" photos and more stimulated by a slow-breathing robot when viewing "low arousal – pleasure" photos.

Further investigation on haptic breathing feedback was presented in [132] where the premise that irregular breathing correlates with low valence (negative emotions) was investigated. Using the small, fur-covered, animal-like FlexiBit robot, breathing conditions were generated of different variability and complexity. Experiments with 10 participants showed correlation was discovered between irregular breathing patterns and low participant ratings of the robot's valence. However, qualitative discussions with participants uncovered rich narratives beyond the above finding about the breathing and valence of the robot, indicating a complex relationship between haptic breathing and participant perceptions of robot affect.

4.3 Task Performance

Nakagawa et al. [133] investigated the effect of touch by a robot on human motivation. In particular, the human-like Robovie-mR2 was used to encourage participants to complete a monotonous task of dragging digital shapes to different regions of a screen. The robot interacted with the participants through one of three different touch conditions: no touch, passive touch (robot requests to be touched), and active touch (unsolicited robot touch of the participant). The active touch scenario nearly doubled both the number of actions taken by the participants and their working time compared to the passive scenario. The researchers acknowledged the ethical issues that might arise around robot touch potentially being used for "bad" purposes in persuasive scenarios that may change human behaviors.

The above experiment was repeated in [134] with the same robot and same conditions, however, expanded upon the data collected. In addition to seeing a repeat in the nearly doubling of the number of actions taken and working time for the active touch scenario compared to the passive and no touch scenarios, information was also collected about accuracy and timing of tasks. Between the three conditions, no significant difference in task accuracy or task completion time was observed. This suggests that while touch may be an effective motivator to work harder and longer, it does not necessarily improve the quality or efficiency of task performance.

In [114], the effects of robot touch were investigated with respect to a person's willingness to donate money to the MDS robot. The MDS robot attempted to encourage participants to donate to charity at a museum setting using either the presence or absence of offering a handshake during the interaction and by varying its voice between male and female. Results showed that participants donated more in the no-handshake condition when the robot was of the opposite sex to the participant, and that they donated more in the handshake condition for same sex human–robot pairings.

4.4 Summary of Haptic Communication

Haptic communication from even simple touch actions from a robot to a human have been shown to help improve cognitive framing of robots with respect to enjoyability [121], positive attitude towards robots, human-likeness [122], pleasantness, and stimulation [130, 131]. In situations where a robot treated a person unfairly, touch was shown to inhibit feelings of negativity towards the robot [123]. A robot was also shown to be suitable for giving a user a head massage, and actually led to the highest levels of user happiness [124].

Preliminary work has been done to investigate the recognition of emotions through a robot's touch [126, 128], though success rates as high as other communication modes have not been achieved. That said, a robot's irregular breathing patterns have been shown to successfully communicate negative valence to users through haptic interaction [132]. Regardless of an individual's ability to recognize a robot's haptic emotion, a robot's simulated haptic breathing has led to increased calmness in users when holding the robot [129].

Though the examples above highlight preliminary findings on haptic communication, further investigation is needed to explore the nuances and intricacies of communication using robotic touch and its influence on people during HRI [32, 135].
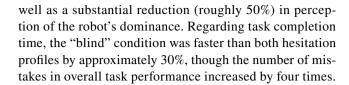
5 Chronemics

The study of chronemics is defined as studying the "non-verbal communication code system concerned with human time-experiencing" [136]. This important research field uncovers the tempo of human interaction and the pace at which we expect communication to occur [25]. Within nonverbal HRI, chronemics has been referenced as a crucial factor in communication [137, 138], however, its study, and specifically how a robot's nonverbal timing influences humans, has been limited. Granted, some aspects of chronemics such as biological time or cultural time are *currently* not relevant to robotics, however to-date, only the study of hesitation in robot action and how it influences people's cognitive framing of robots has been explored.

5.1 Cognitive Framing

Moon et al. [139, 140] investigated how robot hesitation gestures should be used in collaborative tasks to ensure transparency to a user with limited robotic experience. Hesitation gestures are used by people to convey uncertainty [141] and the researchers hoped to explore this phenomenon in HRI. They designed a study that created human-like hesitation gestures for a CRS A460 industrial robot arm and conducted experiments with human–human and human–robot resource conflict scenarios over grabbing an object. Videos of these two scenarios were shown to participants. The participants acknowledged that the intent of the robot gestures could be recognized equivalently to the human gestures, even when only hesitations using the wrist (and not full arm) were used, as well as for more complex movements involving the entire arm.

In [142], the same authors made updates to the robot motion controller to include an Acceleration-based Hesitation Profile (AHP) that more accurately modeled the motion profile of hesitation gestures performed by humans. This condition was tested alongside the original, immediate-stop hesitation profile and a "blind response" that ignored the resource conflict and continued reaching for the resource. Participants again watched videos and participated in physical experiments with the robot. Though participants were able to distinguish between the AHP and immediate-stop motion profiles and acceleration rates, there was little evidence to indicate that the different profile types contributed to a dissimilar cognitive framing of the robot or task completion time. However, both hesitation profiles when compared to the "blind" condition showed similarly significant improvements with respect to safety, animacy, likeability, and anthropomorphism, as

well as a substantial reduction (roughly 50%) in perception of the robot's dominance. Regarding task completion time, the "blind" condition was faster than both hesitation profiles by approximately 30%, though the number of mistakes in overall task performance increased by four times.

5.2 Summary of Chronemics

The few studies to-date that have investigated chronemic communication with robots have focused mainly on robot hesitation gestures. They have found that the intent of these gestures to convey uncertainty is highly recognizable in resource-conflict scenarios [139, 140] and that the use of hesitation gestures, regardless of specific motion profile, has the potential to improve robot safety, animacy, likeability, and anthropomorphism, and lower the perception of dominance [142]. In task performance, hesitation gestures can increase completion time, however, they can also greatly reduce activity errors [142].

6 Multimodal Nonverbal Communication

Sections 2–5 have each investigated one nonverbal communication mode and how it has influenced users during HRI scenarios. In some papers, these modes were combined with verbal communication as well. In this section we investigate the use of robot multimodal nonverbal communication using some combination of the above modes. Multimodal communication is used in everyday human life to transmit more information and provide redundancy, to transmit such information over different distances (i.e. facial expressions for close distances and arm gestures for further distances), and even to change the meaning of one mode of communication by augmenting it with a second mode [143]. We investigate multimodal nonverbal communication with respect to all four influence types: human cognitive framing of robots, emotional recognition and response, human behavioral response, and overall task performance during HRI.

6.1 Cognitive Framing

This subsection investigates how a robot's use of multimodal nonverbal behaviors influence human comfort levels in social interactions involving touch (handshakes), arm gestures and facial expressions, head movements and proxemic distance, and gaze and proxemic distance. Furthermore, the effects of a combination of vocalics and kinesics on persuasiveness and perceived intelligence of a robot are also discussed.

Si and McDaniel [144] investigated the impact of a variety of different robot arm gesture and facial expression conditions with respect to a person's comfort level in social

interactions. They used a Baxter robot with an animated face placed on top of a powered wheelchair. The facial expressions and arm gestures of the robot were designed to either be non-existent, arbitrary, or meaningful to the robot's speech. Participants answered several questions posed by the robot before the robot asked them to approach it and shake its hand (introducing a haptic element). Hesitation to approach the robot when asked was measured as an indicator of comfort level and participants also reported their level of comfort during the interaction. While both facial expressions and gestures had some impact on improving human comfort, arm gestures played a significantly more important role. In addition, reported comfort levels were similar between the arbitrary and meaningful gesture conditions, however, when measuring hesitation, comfort levels were higher in trials involving meaningful behaviors compared to arbitrary.

Demographic factors have also been studied with respect to their relationship to robot proxemic distance and head movements. For example, Takayama and Pantofaru [145] investigated minimum comfortable distance with the PR2 robot in approach scenarios. Their experiments featured two scenarios: (1) a participant approached the robot until reaching a comfortable distance for him/her, and (2) a participant was approached by the robot and stepped aside when he/ she felt uncomfortable. A variety of different factors including pet ownership, previous robot experience, gender, and agreeability were considered. They found that the minimum comfortable distance was smaller for those who owned pets (on average 0.39 m vs. 0.52 m) and those with previous robot experience (on average 0.25 m vs. 0.34 m). In both scenarios described above, they also experimented with robot head orientations during the approach, having conditions where the robot's head was looking directly at the person or facing away. They found that when the head was directly facing a participant, the comfortable distance was closer for men, but larger for women compared to the facing away condition.

Mumm and Mutlu [146] also investigated the impacts of intentionally varying a robot's likeable behavior, and its gaze behavior on a human's physical and psychological distancing. Using the Wakamaru upper-torso humanoid robot, participants played a short game which involved approaching the robot and answering a series of personal questions. The robot's speech was presented as either likeable (polite, empathetic) or unlikeable (rude, selfish), and its gaze condition was either mutual (maintain eye contact) or averted (avoiding the participant). Participants in the unlikeable condition had an increase in physical distance when the robot was gazing at them, while participants in the likeable condition showed no change in distance due to gaze presence. Participants in the unlikeable compared to the likeable condition also had a greater "psychological distance" which the authors measured by the level of personal disclosure to the questions posed by the robot.

In an attempt to design more persuasive robots, [147] created an HRI scenario involving a Desert Survival Problem [148] where participants must rank the importance of a set of items that increase their chance of survival in an imagined crash-landing scenario in the middle of the desert. In this experiment, participants created an initial ranking of the items and a Wakamaru upper-torso humanoid robot attempted to persuade them to change their rankings using speech and four different nonverbal conditions: (1) no nonverbal cues (static and flat voice), (2) vocalic cues only, (3) body cues only, and (4) body and vocalic cues. The body cues included a combination of proxemics (robot entering the participant's personal space), gaze (dynamic eye gaze between the person and the item list), and arm gestures (iconic and deictic gestures congruent with speech). They measured both the success of changing participant item rankings and their impressions of the robot having persuasiveness, intelligence, and providing satisfaction. Compared to the no cues condition, the use of nonverbal cues led to higher levels of persuasion in changing items as observed through changing items. The use of body cues changed an average of 2.5 items and the vocalics condition an average of 1.5 items versus only 1 item change for the no cues condition. Male participants but not female participants evaluated intelligence significantly higher when the robot used body cues, while female participants and not male participants evaluated satisfaction significantly higher when the robot used vocalic cues. However, no significant findings were found on reported levels of persuasion, which is different than the physical actions that the participants took in changing their item rankings.

6.2 Emotional Recognition and Response

Research in emotional recognition and response of multimodal nonverbal communication has focused on how well multimodal behaviors can be recognized when used to display different emotions (e.g., anger, happiness, surprise, disgust, sadness, fear, and perplexity) or how well multimodal behaviors can be used with emotional statements (e.g. "I love you" or "I am feeling awkward").

Zecca et al. [149] used robot body postures and facial expressions for displaying the emotions of anger, happiness, surprise, disgust, sadness, fear, and perplexity on the KOB-IAN humanoid robot. Participants watched videos of KOBIAN displaying these emotions either through each mode individually or using a combination of the two modes. They were then asked to identify each emotion. Body posture had a low average recognition rate of 33.8% with only sadness and perplexity having a rate over 50%. Robot facial expressions were marginally more successful with an average recognition rate of 44.6%, with happiness, surprise, and disgust having a rate of more than 50%. However, together, the

combined body postures and facial expressions had a 70% average recognition rate with only happiness being recognized less than 50%.
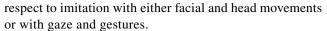
Li and Chignell [150] investigated the interpretation of emotional intent with the teddy bear robot, RobotPHONE, capable of only simple head movements and arm gestures. They asked an initial set of participants to generate a variety of head and arm movements associated with emotional statements such as "I am happy", "I love you", or "I am feeling awkward," by manipulating the head and arms of the robot. These movements were then presented back by the robot to a separate set of participants who were asked to identify them. Participants were able to recognize emotional intent better than chance through the simple head and arm movements of RobotPHONE. A second study described in the paper had two sets of participants (puppeteers and amateurs) develop head and arm gestures on RobotPHONE for the six primary emotions (e.g., anger, disgust, fear, happiness, sadness, and surprise).When presented to another set of participants, average recognition rates were higher for the puppeteer's behaviors compared to the amateur's, particularly for disgust and fear, showing the value of expertise in developing these types of behaviors.

In [151], Erden developed emotional postures on the NAO robot for the three emotions of anger, sadness, and happiness. Namely, a qualitative description and encoding of human emotional behaviors guided the development of 32 postures involving arm, head, and body movements. These were narrowed to the top five for each emotion by a group of 25 participants. Then 40 participants attempted to identify each emotional posture using Ekman's six primary emotions [152]. The success rates were 45% for anger, 63% for sadness, and 73% for happiness.

A study by Gacsi et al. [153] investigated the attribution of emotions to a robot displaying multimodal behaviors. A PeopleBot telepresence robot was used for the study and was affixed with two arms on either side: one was a five DoF robotic arm, the other, non-moveable. Five behavior sets—joy, fear, neutral, sadness, and anger—involving movement, turning, and arm gestures were developed for the robot based on dog behaviors. Participants were shown videos of both the robot and a dog displaying behaviors associated with the different emotional conditions and asked to guess the emotions. Correct answers were obtained for both robot and dog behaviors significantly better than chance, and the robot was even recognized more successfully than the dog for the emotion of anger (75% robot, 58% dog).

6.3 Behavioral Response

The research below explores how robot multimodal nonverbal behaviors influence the behaviors of people, with respect to imitation with either facial and head movements or with gaze and gestures.

Riek et al. [154] conducted an experiment to observe the influence of facial expression imitation and head movements on a participant's behaviors. They used the Wow-Wee Alive Chimpanzee Robot with 18 DoFs in its head/face. They presented participants with a set of verbal questions and, as they responded, the robot mimicked them in one of three ways: blinking only, nodding gestures only, or full head/face mimicry. They counted the number of head, body, hand, and sound behaviors participants made during the interaction and asked them about their satisfaction with the robot. Results found that the blinking only condition elicited the largest number of participant responses (104), compared to the nodding condition (76), or full mimic condition (58), though the difference between blinking and nodding conditions was solely due to an increase in hand gestures by the participant. Reported satisfaction rates were also highest for the blinking only condition. A potential explanation for the success of the blinking-only condition is that some participants reported that many of the robot head and face movements in the full mimicry condition felt "machine-like" and "unclear."

Iio et al. [155] explored the concept of entrainment: a person's tendency to imitate the behavior of the robot with whom they are interacting. Participants were asked to select an object from several objects in front of them and the WoZ controlled Robovie-R v2 humanoid robot was used to confirm their selection. The robot spoke and either used gaze only, gestural pointing only, or gaze and pointing together to confirm. They found that entrainment was the highest in the gazing and pointing condition (81 participant behaviors), slightly less with the gaze only condition (69 behaviors), and lowest with the pointing only condition (52 behaviors). Questionnaire results showed that naturalness and ease of instruction and understanding was highest for the gaze and pointing condition, potentially explaining the reason for increased entrainment.

A large-scale study [156] was conducted to investigate how different nonverbal cues impact the social engagement of participants when listening to a robot telling a story. The MDS robot was programmed to tell stories to a large public crowd under conditions with increasingly animated multimodal cues: audio alone, adding lip motions, adding facial expressions, and adding arm gestures. Participants were determined to be fully engaged if they were present and facing the robot during the entire story. The engagement levels of participants increased with the addition of lip movement sand arm gestures However, engagement was approximately the same when facial expressions were used compared to audio alone.

6.4 Task Performance

This subsection explores how multimodal robot behaviors influence human performance in tasks concerning either completion time or memory retention.

Boucher et al. [157] investigated the effects of head movements and eye gaze on cooperative task completion, using the iCub child-like robot. The robot asked participants to search for a specific object on a table in front of them while the robot used either the presence or absence of head movements (towards object or none) and eye gaze (eyes covered or towards object) in guiding the search task. When compared to the null condition (no head movements or eye use), it was found that both head movements and eye gaze as well as head-only movements improved participant task completion time by similar amounts. They both also improved reaction time to the point of helping a participant anticipate upcoming tasks before a verbal command was completed. Eye-only movements had similar reaction and task completion times to the null condition.

To investigate gesturing and gaze effects on information recall and task completion, Admoni et al. [158] created a collaborative task where participants followed directions issued by a NAO robot under different conditions. The robot issued a set of block assembly instructions that the participant had to carry out under a variety of conditions. The difficulty of the task was varied with either a low or high memorization load and the presence or absence of an interruption during the task. The robot also varied its behavior in conditions where nonverbal behaviors of gazing and pointing at blocks while providing instructions were present or absent. Participants completed multiple assemblies before answering a questionnaire on robot anthropomorphism, animacy, likeability, and intelligence. When the task was easy, the presence of nonverbal behaviors had little influence over both recall and completion time, however, when difficulty increased due to either additional steps or interruption, the nonverbal behaviors led to higher recall accuracy and lower completion times. That said, none of the questionnaire metrics were influenced significantly between the different nonverbal behavior conditions.

Kennedy et al. [159] attempted to explore the impact of nonverbal immediacy on learning. Nonverbal immediacy is defined as the enhancing of closeness to and interaction with another [160]. A storytelling scenario between a human and NAO robot was investigated with the robot using a combination of arm gestures, gaze, and body orientation. These were varied between high (animated) and low (absent or subdued) nonverbal immediacy. Findings showed that both children and adults could distinguish between the robot's high and low immediacy conditions. While higher nonverbal immediacy (more animated behaviors) improved story retention

with children, it made no difference for adults, possibly due to the low complexity of the task.

In [161], Lohse et al. investigate the perceived workload and task performance of participants when interacting with a NAO robot for an information recall task. Participants were guided through either an easy or a difficult direction-giving task by the robot who gave instructions either with or without the use of arm and head gestures. Their results showed that participants recalled more directions in both the easy and difficult tasks when the robot used gestures over no gestures. In addition, participants reported significantly lower mental workload in the gestures condition for both task difficulties.

McCallum and McOwan [162] explored the effects of nonverbal communication on long-term engagement when playing music with Mortimer, an upper-torso humanoid drumming robot. Participants spent 6 weeks playing music with Mortimer for between 20 and 45 min per week in one of two conditions: with or without the robot's use of facial expressions and head poses. Results showed that those subjected to nonverbal behaviors spent more time voluntarily with Mortimer, and actually increased the time they spent with the robot with passing weeks. In addition, these participants interrupted the robot less during social interactions and played music with the robot uninterrupted for longer periods. The authors believed that the use of nonverbal behaviors in Mortimer provided musical guidance that led to more engaged, uninterrupted task performance.

6.5 Summary of Multimodal Nonverbal Communication

Multimodal nonverbal behaviors have shown to be effective influencers of people's cognitive frames. The use of robot arm gestures and facial expressions were shown to improve comfort levels in HRI [144]. However, the combination of gaze and proxemic distance appeared to be more complex; comfort levels tended to increase with gaze presence for men, pet owners [145], and those presented with "likeable" robots [146], but decreased for women [145] and individuals presented with "unlikeable" robots [146]. In attempting to make a more persuasive robot, the use of arm, gaze, and proxemic cues greatly increased persuasion effectiveness for participants even though their subjective ratings of persuasion were unaffected [147].

In general, multimodal displays of nonverbal communication have shown to have higher emotional recognition rates than unimodal nonverbal communication [149, 150]. One study showed that multiple configurations of arm, head, and body postures can all be recognized as human emotions effectively [151]. Another even showed that emotions expressed through multimodal behaviors designed from dog

movements can be recognized better than chance and sometimes even better than the dog [153].

Regarding task performance, the use of multimodal behaviors led to improvements in reaction time and completion time for basic cooperative searching tasks [157], as well as memory retention, at least for children [159]. Adult memory performance was less influenced by multimodal nonverbal behaviors in simple tasks [158, 159], however, in more difficult tasks, the use of these behaviors increased both recall accuracy and completion time [158]. Information recall was shown to be higher in direction-giving tasks when a robot provided guidance using arm and head gestures for both easy and difficult tasks [161]. In a long-term study with musicians, participants voluntarily spent more time playing music and played longer uninterrupted when playing music with a robot drummer who employed facial expressions and head poses over the control condition [162].
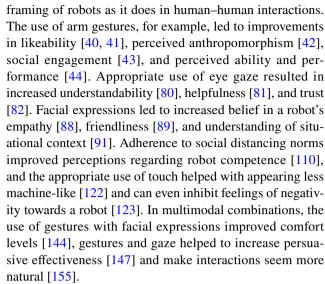
Finally, some interesting discrepancies were found with respect to a robot's influence on human behavior. While experiments on collaboration showed both higher levels of entrainment (behavioral imitation) and more natural interactions with a multimodal gaze/gesture condition [155], conversation-based experiments found that the highest satisfaction rates and highest number of participant gestures were obtained with the lowest level of nonverbal behaviors (blinking only) compared to more animated robot conditions [154]. A storytelling experiment found levels of user engagement were higher when a robot used facial expressions and arm gestures compared to a control condition with voice only [156].

7 Discussion

This survey has resulted in several main findings emerging with respect to how robot nonverbal communication influences people during social interactions. Research across multiple nonverbal modalities has contributed results that can be aligned to the human influence types identified and investigated with respect to shared aims. In this discussion, we will present insights and future research directions associated with each of the aforementioned influence types explored, focusing on key findings, and identifying open challenges that need to be addressed in order to expand the research area and its impact on social HRI.

7.1 Cognitive Framing

Decades of comprehensive research has resulted in a thorough understanding of how different nonverbal behaviors influence the cognitive framing of individuals in human–human interactions [141]. In general, the inclusion of robot nonverbal behaviors that align with human behaviors has shown to have a similar impact on the cognitive

framing of robots as it does in human–human interactions. The use of arm gestures, for example, led to improvements in likeability [40, 41], perceived anthropomorphism [42], social engagement [43], and perceived ability and performance [44]. Appropriate use of eye gaze resulted in increased understandability [80], helpfulness [81], and trust [82]. Facial expressions led to increased belief in a robot's empathy [88], friendliness [89], and understanding of situational context [91]. Adherence to social distancing norms improved perceptions regarding robot competence [110], and the appropriate use of touch helped with appearing less machine-like [122] and can even inhibit feelings of negativity towards a robot [123]. In multimodal combinations, the use of gestures with facial expressions improved comfort levels [144], gestures and gaze helped to increase persuasive effectiveness [147] and make interactions seem more natural [155].

Even though typically, nonverbal behaviors were modeled after humans, some studies found that this approach did not always generate improved cognitive framing around robots. In particular, in a few studies, non-humanlike behaviors such as gestures incongruent to speech [42] or "caricatured", abrupt, and exaggerated head movements [65] were found to be more effective at improving likeability and human-likeness. In psychology research, the pratfall effect is a long-studied phenomenon in human–human interactions whereby the mistakes of another individual can help to humanize them by making them more relatable [163]. Examples of this effect have also been seen with robots. The presence of errors in a robot's verbal questions and instructions to a human were found to make the robot more likeable [164]. In another study [165], cognitive imperfections such as judgmental mistakes, wrong assumptions, or overexcitement, helped to make a robot more relatable and improve long-term interactions [165]. Yet another study in [166] found that a robot's task efficiency was of secondary importance compared to its expressiveness in improving human preference, and that the exhibition of human-like errors may make people reluctant to 'hurt a robot's feelings.' These studies point to a hypothesis that supports findings in [42, 65]; that 'non-humanlike', erroneous behaviors actually *can be* humanizing and relatable, thus improving our cognitive framing of robots.

There were some situations where robot nonverbal behaviors induced negative cognitive framing, particularly with the use of gaze. For example, in social distancing scenarios, the use of a robot's gaze during approach was seen to reduce comfort levels for women [145], but not for men. In similar scenarios, reductions in comfort due to the use of direct gaze at a person were observed for individuals who were initially presented with unlikeable (rude, selfish) robot behaviors [146]. While interacting during a simple game, the use of gaze even added a sort of "social pressure" to rush participants through the game [82]. Given the extensive research

on human–human interactions connecting direct gaze with intimidation and dominance, e.g. [167–169], these findings are understandable, yet still highlight an important takeaway message: robot gaze behavior has the same potential to induce dominance similar to human gaze behavior.

Open Challenges

Challenge 1 Outside of simple metrics such as anthropomorphism, likeability, intelligence, and friendliness, it is not yet clear how different nonverbal behaviors or combinations of these behaviors during interactions can directly influence human cognitive framing of robots. Cognitive frames play a critical role in rapid, high-level, heuristic-based decision making in everyday life [170, 171], including in social interactions (often referred to as 'first impressions' [172]). As such, a better understanding of how robot nonverbal behaviors influence our cognitive frames should have a significant influence on how we judge and make decisions while interacting with robots. To date, most research in this area has focused on understanding the influence of nonverbal behaviors on specific frames, however, future research should focus on how influencing these frames can impact human decision making.

Challenge 2 How humans adapt to robot behaviors over time is still also an open challenge. Given the relative inexperience of the general population with social robots, the length of time of interaction is important to explore in order to investigate how people's cognitive frames of robots could evolve over repeated interactions. Studies investigating interactions over the course of multiple weeks have shown that perceptions of robots change with time and the frequency of interactions [107, 115, 162, 173, 174]. Over weeks of interactions playing chess with a robot, which used facial expressions to react to the game, participant framing of social presence improved with time [174]. Playing music with an expressive drumming robot resulted in participants voluntarily spending more time and engaging in longer uninterrupted play over a series of weeks [162]. In a simulated household environment, participant comfort levels increased over weeks as participants had multiple experiences with a robot in social approach scenarios [107]. In proxemic passing trials, participant comfort levels also increased with experience as the robot passed by a participant multiple times at intimate distances [115]. Though past research has shown examples of a "novelty effect" with robots—people behaving differently in early encounters due to the newness of the system [175]—there may also be an adaptation or trust effect developing with time and multiple interactions. Further investigation is required to better understand the causes of these longitudinal changes as well as how different modes, the combination of modes, and overall robot nonverbal behaviors influence human framing over time.

7.2 Emotion Recognition and Response

The concept of emotion contagion during social HRI was evident across a few different behavior types including arm gestures [48, 49, 176], body and head movements [76], facial expressions [89], and touch [121, 129]. This is an important finding since emotion contagion is considered a "*basic building block of human interaction… allowing people to understand and share the feelings of others*" [177]. Human emotion contagion has been shown to have positive impacts on service satisfaction [178, 179], which will be a critical consideration for social robots performing tasks in service environments such as healthcare, education, entertainment, and retail.

Open Challenges

Challenge 1 It is still not fully clear how robot emotional displays influence human emotional response. A number of papers reviewed herein focused on the recognition of robot nonverbal emotions by users through gestures [51], body movements [66, 69, 70, 72], facial expressions [92–94], haptics [126, 130, 132], and multimodal combinations [149–151, 153], however, only a handful investigated how the recognition of these emotions directly influenced a person's emotional response [48, 49, 76, 89, 121]. Though emotion contagion is a known phenomenon in human–human interactions [180], our understanding of this phenomenon in human–robot interactions is rudimentary. Further understanding of this influence will be useful for designing social robots that appropriately affect human emotions as intended in order for these robots to have a positive impact during service/assistive HRI as mentioned above.

Challenge 2 How an individual's awareness impacts their interpretation of and response to an emotion being communicated by a robot is still an open question. Using similar experimental setups, the researchers in [49, 176] were able to demonstrate the contagion effect both when participants were *able* to identify the intended valence displayed by the robot as well as when they were *unable* to identify the intended valence [48]. However, if there were any differences in the human emotional response due to such awareness, they were not explored. Past research has shown that while human emotional processing occurs largely autonomously, our awareness of the emotion being projected by another person can still influence how the emotion is interpreted [181] and therefore, potentially how we respond to it. Assuming a similar effect may occur with robots, more research into awareness around emotion contagion during HRI is needed.

7.3 Behavioral Response

Of the four influence types investigated in this paper, behavioral influences appear to have the most conflicted findings. In cases involving *simple* interaction scenarios, humans were
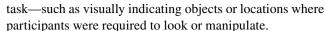
seen to mimic robot behaviors such as arms gestures during object handover [84] and pointing at objects [155]. However, an equal number of examples were seen where users did not behave similarly to robots. Movement synchronization, a common phenomenon during human to human interaction [53], was observed when using an adaptive humanoid NAO robot [54], however, was not observed when using a robot arm [52], likely due to the robot arm showing no adaptation towards the human's movement. In a conversational interaction with a robot monkey head [154], nonverbal behaviors of users (arm gestures, body movements, facial expressions) were *most* plentiful when a robot was in its *least* nonverbally active condition. However, participants also mentioned that they found the robot to be overly machine-like during the interaction. One of the positive examples of mimicry involving object pointing [155] even found that while a human's mimicry was high for a robot's gaze and pointing condition, this level dropped by more than half when the robot only pointed and there was no gaze used. The authors postulated that this happened since the pointing-only condition was not how a human would show attention towards an object and the interaction did not feel natural. While further investigation is required, there seems to be a connection between a person's perception of a robot (in particular, with respect to naturalness and human/machine-likeness) and their behavioral response to the robot during interaction.

Open Challenges
Challenge 1 The relationship between a person's behavioral responses to a robot's nonverbal behaviors and how the robot is perceived during an interaction has not been explicitly investigated. Nonverbal behavioral responses (such as gestural mimicry mentioned above) are ubiquitous in human to human interactions [182] and influence the outcome of liking, rapport, affiliation, and empathy between two individuals [183]. However, as previously mentioned, human behavioral responses to robots appear to be correlated to our perception of robots on metrics of naturalness, machine-likeness, and possibly others. A better understanding of this correlation would allow us to design robot behaviors that illicit natural human behavioral responses and, in theory, also influence the liking, rapport, affiliation, and empathy levels between a human and a robot.

7.4 Task Performance

Across numerous task types, a robot's nonverbal behaviors were shown to have significant influences on improving human performance. A number of the papers surveyed found a decrease in human task performance time with the use of robot eye gaze [80, 81, 83, 157], gestures [56, 158], or facial expressions [100]. These behaviors were primarily effective for functional reasons—practical and directly specific to the task—such as visually indicating objects or locations where participants were required to look or manipulate.

There were also a handful of papers that observed influences on task performance due to psychosocial reasons; those relating to the mental and emotional states of a person and the interrelation of these states with social factors [184]. For example, a robot's gaze at a participant during a gaming task was believed to cause a sort of social pressure that lowered trust and rushed participants to respond [82]. Sad facial expressions on a robot were seen to increase the engagement time for people interacting with an expressive robot [96]. A more nonverbally expressive musical robot led to longer jam sessions with people, likely due to the rhythmic connections formed [162]. Robot touch was used to encourage human productivity by doubling working time and the number of tasks completed [133]. Touch in the form of a robot handshake also caused people to donate more money, so long as the robot had the same gender as the participant [114]. Fear and negative mood displayed through robot body movements encouraged participants to comply with evacuation requests faster [76].

Open Challenges
Challenge 1 Regarding functional influences on human task performance by robot nonverbal behavior, there is still limited understanding of influence across different behavior types as well as the implications of these behaviors on various performance metrics. The main focus has been on the influence of gaze [80, 81, 83, 157], gestures [56, 158], facial expressions [100], body movements [76], and touch [133] on task time. The influence of proxemics, chronemics, and multimodal nonverbal behaviors has yet to be explored with respect to human task performance. While memory retention [57, 158, 159, 161] and error reduction [77, 80, 142] have been researched as performance metrics, as previously mentioned, task time [56, 80, 81, 83, 100, 157, 158] has received the majority of the focus. Other metrics, such as mental workload and situation awareness, have been identified as potentially important to human task performance in HRI [185]. Mental workload has been investigated with respect to robot speed in an industrial environment [186], and with respect to interface design with telepresence robots [187]. Situation awareness has been explored in urban search and rescue [188, 189], and general telerobotic use [190, 191]. However, neither metric has been studied with respect to robot nonverbal communication, particularly in social settings. These metrics will become increasingly important to understand with respect to nonverbal communication as human–robot collaboration continues to proliferate in more social environments such as healthcare, home service, and entertainment [192].

Challenge 2 It is important to investigate how robot nonverbal behaviors can have psychosocial influences on human task performance. Human–human research has shown that

Table 1 Summary of surveyed papers, including author(s), modality, influence type, number of subjects, year, and robot details

References	Sec.	Modality	Influence	Robot Name	Robot Type	Height (cm)	Robot DoF	Subjects	Year
Salem et al. [40]	2.1	Arm Gestures	Framing	ASIMO	Humanoid with 2 arms, 2 legs, head	130	34	40	2011
Salem et al., [41]	2.1	Arm Gestures	Framing	ASIMO	Humanoid with 2 arms, 2 legs, head	130	34	62	2013
Salem et al., [42]	2.1	Arm Gestures	Framing	ASIMO	Humanoid with 2 arms, 2 legs, head	130	34	60	2012
Aly and Tapus [43]	2.1	Arm Gestures	Framing	NAO	Humanoid with 2 arms, 2 legs, head	57	25	21	2016
Shen et al. [44]	2.1	Arm Gestures	Framing	KASPAR2	Humanoid with 2 arms, 2 legs, head	*N.R.*	18	23	2015
Peter et al. [45]	2.1	Arm Gestures	Framing	NAO	Humanoid with 2 arms, 2 legs, head	57	25	101	2017
Xu et al. [48]	2.1	Arm Gestures	Emotion	NAO	Humanoid with 2 arms, 2 legs, head	57	25	34	2014
Xu et al. [49]	2.1	Arm Gestures	Emotion	NAO	Humanoid with 2 arms, 2 legs, head	57	25	36	2015
Xu et al. [50]	2.1	Arm Gestures	Emotion	NAO	Humanoid with 2 arms, 2 legs, head	57	25	24	2013
English et al. [51]	2.1	Arm Gestures	Emotion	NAO, Mini Darwin	Humanoid with 2 arms, 2 legs, head	57	25	137	2017
Lorenz et al. [52]	2.1	Arm Gestures	Behavior	*N.R.*	Upper-torso Humanoid	*N.R.*	7	8	2013
Lorenz et al. [53]	2.1	Arm Gestures	Behavior	*N.R.*	Upper-torso Humanoid	*N.R.*	7	20	2012
Ansermin et al. [54]	2.1	Arm Gestures	Behavior	NAO	Humanoid with 2 arms, 2 legs, head	57	25	9	2017
Ende et al. [55]	2.1	Arm Gestures	Behavior	DLR Humanoid, DLR LWR SAM	Upper-torso humanoid with 2 arms, industrial arm	*N.R.*	7 (1 arm)	400	2011
Riek et al. [56]	2.1	Arm Gestures	Task	BERT1	Upper-torso Humanoid with 2 arms, head	*N.R.*	36	16	2010
Dijk et al. [57]	2.1	Arm Gestures	Task	NAO	Humanoid with 2 arms, 2 legs, head	57	25	12	2013
Sheikholeslami et al. [58]	2.1	Arm Gestures	Task	Barrett WAM	Industrial Arm	*N.R.*	7	4	2017
Quintero et al. [59]	2.1	Arm gestures	Task	Barrett WAM	Industrial Arm	*N.R.*	7	8	2015
Hoffman et al. [62]	2.2	Body and head movements	Framing	Kip1	Lamp-like, articulated head	30	3	30	2015
Rosenthal-von der Putten et al. [63]	2.2	Body and head movements	Framing	NAO	Humanoid with 2 arms, 2 legs, head	57	25	80	2018

Table 1 (continued)

References	Sec.	Modality	Influence	Robot Name	Robot Type	Height (cm)	Robot DoF	Subjects	Year
Choi et al. [64]	2.2	Body and head movements	Framing	*N.R.*	Telepresence with screen, wheel base	*N.R.*	2	36	2017
Wang et al. [65]	2.2	Body and head movements	Framing	Nico	Upper-torso Humanoid	*N.R.*	14	39	2006
McColl and Nejat [66]	2.2	Body and head movements	Emotion	Brian 2.0	Upper-torso Humanoid	*N.R.*	13	50	2014
Embgen et al. [69]	2.2	Body and head movements	Emotion	Daryl	Upper-torso Humanoid	*N.R.*	10	29	2012
Saerbeck and Bartneck [70]	2.2	Body and head movements	Emotion	iCat	Toy Cat with articulated head	40	13	18	2010
Beck et al. [72]	2.2	Body and head movements	Emotion	NAO	Humanoid with 2 arms, 2 legs, head	57	25	26	2010
Beck et al. [73]	2.2	Body and head movements	Emotion	NAO	Humanoid with 2 arms, 2 legs, head	57	25	24	2011
Beck et al. [74]	2.2	Body and head movements	Emotion	NAO	Humanoid with 2 arms, 2 legs, head	57	25	24	2013
Beck et al. [75]	2.2	Body and head movements	Emotion	NAO	Humanoid with 2 arms, 2 legs, head	57	25	23	2010
Moshkina [76]	2.2	Body and head movements	Task	NAO	Humanoid with 2 arms, 2 legs, head	57	25	48	2012
Van Den Brule et al., [77]	2.2	Body and head movements	Task	NAO	Humanoid with 2 arms, 2 legs, head	57	25	56	2016
Breazeal et al. [80]	2.3	Eye gaze	Task	Leonardo	Zoomorphic with 2 arms, 2 legs, head	*N.R.*	65	21	2005
Skantze et al. [81]	2.3	Eye gaze	Task	Furhat	Head with projected face	*N.R.*	3	24	2013
Stanton and Stevens [82]	2.3	Eye gaze	Task	NAO	Humanoid with 2 arms, 2 legs, head	57	25	59	2014
Moon et al. [83]	2.3	Eye gaze	Task	PR2	Wheeled base with 2 arms, head	133	22	102	2014
Zheng et al. [84]	2.3	Eye gaze	Task	PR2	Wheeled base with 2 arms, head	133	22	102	2014
Gonsior et al. [88]	2.4	Facial expression	Framing	EDDIE	Articulated head	*N.R.*	23	55	2011
Leite et al. [89]	2.4	Facial expression	Framing	iCat	Toy Cat with articulated head	40	13	40	2013
Endrass et al. [90]	2.4	Facial expression	Framing	Alice	Humanoid with 2 arms, 2 legs, head	*N.R.*	22	96	2014
Hegel et al. [91]	2.4	Facial expression	Framing	BARTHOC Jr.	Upper-torso humanoid with 2 arms, head	65	10	28	2006
Berns and Hirth [92]	2.4	Facial expression	Emotion	ROMAN	Articulated head	*N.R.*	10	32	2006
Kobayashi et al. [93]	2.4	Facial expression	Emotion	Face Robot Mk II	Articulated head	*N.R.*	24	20	2003

Table 1 (continued)

References	Sec.	Modality	Influence	Robot Name	Robot Type	Height (cm)	Robot DoF	Subjects	Year
Allison et al. [94]	2.4	Facial expression	Emotion	Brian	Upper-torso humanoid with 2 arms, head	*N.R.*	20	10	2009
Cameron et al. [95]	2.4	Facial expression	Emotion	Zeno R50	Humanoid with 2 arms, 2 legs, head	*N.R.*	*N.R.*	59	2018
Gordon and Breazeal [96]	2.4	Facial expression	Behavior	Dragonbot	Toy with screen face and passive limbs	*N.R.*	*N.R.*	*N.R.*	2014
Chevalier et al. [98]	2.4	Facial expression	Behavior	Zeno R50	Humanoid with 2 arms, 2 legs, head	*N.R.*	*N.R.*	15	2017
Pour et al. [99]	2.4	Facial expression	Behavior	Alice	Humanoid with 2 arms, 2 legs, head	*N.R.*	22	14	2018
Reyes et al. [100]	2.4	Facial expression	Task	Golem-III	Wheeled humanoid with 2 arms, head	*N.R.*	8	15	2016
Hamancher et al. [101]	2.4	Facial expression	Task	BERT2	Upper-torso humanoid with 2 arms, head	*N.R.*	14	23	2016
Cohen et al. [102]	2.4	Facial expression	Task	iCub	Humanoid with 2 arms, 2 legs, head	120	53	44	2017
Walters et al. [106]	3.1	Social distance	Framing	Peoplebot	Telepresence with screen, wheeled base	110	2	28	2005
Walters et al. [107]	3.1	Social distance	Framing	Peoplebot	Telepresence with screen, wheeled base	110	2	7	2011
Shi et al. [108]	3.1	Social distance	Framing	Segway RMP 200	Wheeled base	152	2	5	2008
Mead and Mataric [109]	3.1	Social distance	Framing	Bandit	Wheeled humanoid with 2 arms, head	130	19	160	2015
Mead and Mataric [110]	3.1	Social distance	Framing	PR2	Wheeled base with 2 arms, head	133	22	40	2016
Koay et al. [111]	3.1	Social distance	Task	Care-O-bot 3	Wheeled base with 1 arm	145	9	19	2014
Kim and Mutlu [112]	3.1	Social distance	Task	Wakamaru	Wheeled humanoid with 2 arms, head	100	13	32	2014
Papadopoulos et al. [113]	3.1	Social distance	Task	NAO	Humanoid with 2 arms, 2 legs, head	57	14	80	2016
Siegel [114]	3.1	Social distance	Task	MDS	Wheeled humanoid with 2 arms, head	122	38	340	2009
Pacchierotti et al. [115]	3.2	Social transit	Framing	Peoplebot	Telepresence with screen, wheeled base	110	2	10	2006
Butler and Agah [116]	3.2	Social transit	Framing	Nomadic Scout II	Wheeled base	170	2	40	2001
Tsui et al. [117]	3.2	Social transit	Framing	Kyosh Blizzard, iRobot ATRV-Jr, Custom Wheel-chair	Wheeled base	*N.R.*	2	224	2010
Gockley et al. [118]	3.2	Social transit	Framing	Grace RW1 B21 Base	Wheeled base	*N.R.*	2	10	2007
Chen et al. [121]	4	Haptics	Framing	Cody	Wheeled base with 2 arms, head	*N.R.*	17	63	2011

Table 1 (continued)

References	Sec.	Modality	Influence	Robot Name	Robot Type	Height (cm)	Robot DoF	Subjects	Year
Cramer et al. [122]	4	Haptics	Framing	Robosapien	Humanoid with 2 arms, 2 legs, head	*N.R.*	*N.R.*	119	2009
Fukuda et al. [123]	4	Haptics	Framing	robovie-mR2	Upper-torso humanoid with 2 arms, head	42	11	15	2012
Walker and Bartneck [124]	4	Haptics	Framing	NAO	Humanoid with 2 arms, 2 legs, head	57	25	18	2013
Willemse et al. [125]	4	Haptics	Framing	NAO	Humanoid with 2 arms, 2 legs, head	57	25	39	2017
Yohanan and MacLean [126]	4	Haptics	Emotion	Haptic Creature	Stuffed Toy	33	1	30	2012
Yohanan and MacLean [128]	4	Haptics	Emotion	Haptic Creature	Stuffed Toy	33	1	32	2011
Sefidgar et al. [129]	4	Haptics	Emotion	Haptic Creature	Stuffed Toy	33	1	38	2016
Yoshida and Yonezawa [130]	4	Haptics	Emotion	BREAR	Stuffed Toy	25	5	26	2016
Yoshida and Yonezawa [131]	4	Haptics	Emotion	NA	Stuffed Toy	55	1	47	2017
Bucci et al. [132]	4	Haptics	Emotion	FlexiBit	Stuffed Toy	*N.R.*	1	10	2018
Nakagawa et al. [133]	4	Haptics	Task	robovie-mR2	Upper-torso humanoid with 2 arms, head	42	11	30	2011
Shiomi et al. [134]	4	Haptics	Task	robovie-mR2	Upper-torso humanoid with 2 arms, head	42	11	33	2017
Siegel [114]	4	Haptics	Task	MDS	Wheeled humanoid with 2 arms, head	122	38	340	2009
Moon et al. [139]	5	Chronemics	Framing	CRS A460	Industrial Arm	*N.R.*	6	30	2010
Moon et al. [140]	5	Chronemics	Framing	CRS A460	Industrial Arm	*N.R.*	6	86	2011
Moon et al. [142]	5	Chronemics	Framing	CRS A460	Industrial Arm	*N.R.*	6	33	2013
Si and McDaniel [144]	6	Face, arms	Framing	Baxter	Upper-torso humanoid with 2 arms, head	91	15	43	2016
Takayama and Pantofaru [145]	6	Distance, gaze	Framing	PR2	Wheeled base with 2 arms, head	133	22	30	2009
Mumm and Mutlu [146]	6	Distance, gaze	Framing	Wakamaru	Wheeled humanoid with 2 arms, head	100	13	60	2011
Chidambaram et al. [147]	6	Distance, gaze, arms	Framing	Wakamaru	Wheeled humanoid with 2 arms, head	100	13	32	2012
Zecca et al. [149]	6	Face, body	Emotion	KOBIAN	Humanoid with 2 arms, 2 legs, head	140	48	33	2009
Li and Chignell [150]	6	Head, arms	Emotion	RobotPHONE	Stuffed Toy	*N.R.*	6	12	2011
Erden [151]	6	Head, arms, body	Emotion	NAO	Humanoid with 2 arms, 2 legs, head	57	25	40	2013
Gacsi et al. [153]	6	Body, arm	Emotion	PeopleBot	Telepresence with screen, wheeled base	110	2	81	2016
Riek et al. [154]	6	Face, head	Behavior	WowWee Chimpanzee	Articulated animal head	*N.R.*	18	12	2010

Table 1 (continued)

References	Sec.	Modality	Influence	Robot Name	Robot Type	Height (cm)	Robot DoF	Subjects	Year
Iio et al. [155]	6	Gaze, arms	Behavior	robovie-mR2	Upper-torso humanoid with 2 arms, head	42	13	18	2011
Moshkina et al. [156]	6	Face, arms	Behavior	MDS	Wheeled humanoid with 2 arms, head	122	38	2165	2014
Boucher et al. [157]	6	Head, gaze	Task	iCub	Humanoid with 2 arms, 2 legs, head	120	53	5	2012
Admoni et al. [158]	6	Arms, gaze	Task	NAO	Humanoid with 2 arms, 2 legs, head	57	25	46	2016
Kennedy et al. [159]	6	Arms, gaze, body	Task	NAO	Humanoid with 2 arms, 2 legs, head	57	25	117	2017
Lohse et al. [161]	6	Head, arm	Task	NAO	Humanoid with 2 arms, 2 legs, head	57	25	32	2014
McCallum and McOwan [162]	6	Face, head	Task	Mortimer	Upper-torso humanoid with 2 arms, head	*N.R.*	5	10	2015

NR stands for "not reported", indicating that such details were not reported in the original paper by the authors

people can use nonverbal behaviors to psychosocially influence the actions of others through dominance [193] and persuasion [194]. This can ultimately lead to improved task performance or task compliance. Though the HRI papers surveyed herein showed performance influences on metrics such as evacuation compliance [76], donation solicitation [114] response time [82, 157], engagement time [96, 162], and working time [133], the psychosocial justification of these influences are largely speculative. By having a better understanding of the reasons for these forms of influence (dominance, persuasion, reciprocity, etc.) we can aim to design robots with nonverbal behaviors that can positively influence human performance through psychosocial means.

7.5 Comparison of Study Parameters Used

It is valuable to compare specific study parameters used when considering findings and conclusions across papers that include a variety of methodologies and materials. As such, we have created Table 1 which summarizes some of the key aspects of the studies reviewed including behavior modality, influence type, number of participants in the study, study year, and details about the robotic platform used (e.g. type, size DoF).

Though the statistical significance of findings for papers throughout this survey has been reported, for studies with low-participant numbers, it is important to consider the findings as exploratory. While they do provide some insight into human–robot interaction and nonverbal influence, they need to be further investigated and validated.

With respect to robot functionality, as previously identified, people tend to prefer more dynamic, animated robot behaviors [43]. This is important to note as it can give robots with a higher number of DoFs an advantage when influencing people for their ability to be more animated in their motion.

Arguably of greater importance is the consideration of the robot type and size used in experiments. Numerous studies have shown that robot embodiment [117, 195, 196], appearance [197, 198], level of anthropomorphism [199–201], and presence [202, 203], can all have an impact on the perception and influence of a robot in social settings. We did not focus on robot presentation in this survey paper as our objective was to investigate the use of movement-based nonverbal communication during social HRI. However, with that said, when comparing findings across multiple robot platforms, the type and size of robot used should be considered. While the majority of studies presented herein used humanoid platforms, some findings may be influenced by subtle nuances of a robot's design.

As an example of this, [117] showed that regardless of the robot used between a Kyosho Blizzard, a mobile ATRV-Jr, and a robotic wheelchair, participants found passing behaviors where the robot stopped for the human the most polite and trustworthy, however, indicated that they were most comfortable with the wheelchair. Another study on social passing [116] with a Nomadic Scout II robot found that a stopping behavior actually lowered participant comfort levels. The discrepancy in these findings may be due to

differing methodologies or they could be due to differences in the robot presentations.

Though influence due to robot presentation was not explicitly considered in this survey, it is an important and thoroughly researched topic [195–208] that warrants a survey paper of its own.

Compliance with Ethical Standards

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

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