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What's in a Name and/or a Frame? Ontological Framing and Naming of Social Actors and Social Responses

David Westerman[1], Michael Vosburg[2], Xinyue "Gordon" Liu[1], and Patric R. Spence[3]

1 Department of Communication at North Dakota State University, Fargo, North Dakota, USA
2 Department of Mass Communication at Benedict College, Columbia, South Carolina, USA
3 Nicholson School of Communication and Media, University of Central Florida, Orlando, Florida, USA

Abstract

Artificial intelligence (AI) is fundamentally a communication field. Thus, the study of how AI interacts with us is likely to be heavily driven by communication. The current study examined two things that may impact people's perceptions of socialness of a social actor: one nonverbal (ontological frame) and one verbal (providing a name) with a 2 (human vs. robot) × 2 (named or not) experiment. Participants saw one of four videos of a study "host" crossing these conditions and responded to various perceptual measures about the socialness and task ability of that host. Overall, data were consistent with hypotheses that whether the social actor was a robot or a human impacted each perception tested, but whether the social actor named themself or not had no effect on any of them, contrary to hypotheses. These results are then discussed, as are directions for future research.

Keywords: social robots, artificial intelligence, electronic propinquity, perceived humanness, attraction, source credibility

Introduction

Artificial intelligence (AI) is fundamentally a communication field (Gunkel, 2020). Dating back to the classic foundations of AI, what has come to be known as the Turing Test (1950),

CONTACT David Westerman • david.k.westerman@ndsu.edu • Department #2512 • P.O. Box 6050 • Fargo, ND 58108

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or how we come to perceive *artificial intelligence* as simply *intelligence*, is driven by how a social actor communicates. Thus, the study of how AI interacts with us is likely to be heavily driven by communication (Westerman et al., 2020). But what seems human, in both humans and AI such as robots? This study examined two ways a robot may communicate its socialness to us; one nonverbal (ontological frame) and one verbal (providing a name) to help address how each may be important for establishing initial perceptions of socialness.

Social Responses to Social Actors

As Turing (1950) suggested, people's perceptions of AI will drive their response to it. Turing specifically suggested that the best way for an AI to pass what became known as the Turing Test would be to use what we today might call text-only computer-mediated communication (CMC); to use only words and not be seen. Seeing an entity is one of the most significant ways to be tipped off that the social actor is not human. Guzman (2020) and A. Edwards (2018) argued that these ontological boundaries of origin are becoming more complicated and vital to consider (see also Etzrodt & Engesser, 2021). Constructivist approaches to communication suggest that social interactions "unfold first and foremost through a process of prototyping the potentially communicative other (what is it?)," which links to stereotyping processes (what does it do?), which then influence perception and messaging, and behavior by driving the creation and use of interaction scripts (A. Edwards, 2018, p. 45). When people interact with other people, they occupy the same ontological space (Dautenhahn, 2004). However, previous studies have demonstrated that both verbal and visual primes suggesting the nature of an actor as a robot versus a human lead to lower expectations regarding interaction sociality such as social presence/electronic propinquity and liking (e.g., A. Edwards et al., 2019) and that ontological/agent-type category cueing can activate heuristics affecting interpretations of agent behavior (e.g., Banks et al., 2021).

Initial interactions are largely driven by our expectations of such interactions, and much about those expectations are scripted (Kellerman, 1992). One such relevant script that has been identified is the human-human interaction script (A. Edwards et al., 2019; C. Edwards et al., 2016; Spence et al., 2014). In general, this script suggests that when people communicate, they expect their partner to be human. When that partner is not human, people have lower expectations about how much social presence/electronic propinquity they will feel in the interaction (A. Edwards et al., 2019; C. Edwards et al., 2016; Spence et al., 2014). Electronic propinquity can be defined as a "psychological feeling of nearness" (Walther & Bazarova, 2008, p. 624) or even more simply as "electronic presence" (Korzenny, 1978, p. 7). Kelly and Westerman (2016) have argued that electronic propinquity is similar to/the same as some other concepts, such as social presence and perceived immediacy, and suggests an experience of interpersonal connectedness between two social actors and the degree of realness perceived in one's communication partner. Thus, if a person is greeted by a robot rather than a human, we expect to see the same perceptions. But even before that, we would also expect a human to be perceived as more human than a robot when that actor is seen. This leads to the first two hypotheses of the current study:

H1: A human will be perceived as more human than a robot.

H2: A human will be perceived as having more electronic propinquity than a robot.

The human-human interaction script predicts social perceptions of initial interactions with robots compared to humans. It may also help suggest possibilities for more task-based initial perceptions, such as task attraction and source credibility, in a similar way. Because the human-human interaction script involves initial encounters, perceptions and attributions may follow similar patterns to what has been seen in psychological research (see A. Edwards et al., 2019). Several studies have found task and social attraction to manifest in communication with humans and machines and impact these perceptions of the communicator. For example, a study by Beattie et al. (2020) examined differences in perceptions of a message sender using emojis when the identity of the message sender was either a human or a chatbot. Emoji use was perceived as more socially attractive than non-emoji use, whether the source was a human or a chatbot.

Cross-cultural studies and studies on stereotypes (in-group vs. outgroups) have shown that "others" are often stereotyped negatively as cold and incompetent (Lee & Fiske, 2006). Task attraction is related to competence, it has been noted that competence refers to capability reflecting the targets' ability to put their intentions into practice (Cuddy et al., 2007). Thus, there may be differences in perceptions of task attraction based on the perception of similarity if the target is a human or robot. Task attraction is defined by McCroskey and McCain (1974) as "how easy or worthwhile working with someone would be" (p. 266). If people's expectations about an initial interaction are violated, this may create uncertainty (Burgoon, 1993), leading to lower perceptions about how easy it may be to work with a partner, and thus, lower task attraction, in line with other perceptions related to the human-human interaction script. Moreover, there may be tasks that are viewed as appropriate for a machine in a given context whereas some tasks might be seen as best completed by a human. There still exists as perception of human-to-human communication as the "gold standard" of communication (Spence, 2019). Following this logic, two studies by Spence et al. (2019, 2021) examined these perceptions in the context of weather forecasts. The first study (Spence et al., 2019) had conditions that included a professional meteorologist's X feed (Twitter), the X feed of a weatherbot, and that of an amateur meteorologist. That study found that respondents perceived the professional meteorologist as more socially attractive than the weatherbot, with no differences in task attraction. The weatherbot was perceived as more task attractive than the amateur meteorologist with no difference in social attraction. The second study (Spence et al., 2021) employed a weather forecast from a local television station using a professional meteorologist, a television station weather robot, and an amateur weather forecaster. Respondents in that study indicated the highest perceptions of task and social attraction with the professional meteorologist followed by the amateur weather forecaster, and the weather robot creating the lowest levels of task and social attraction. The authors argue their results across the two studies taken together support the anthropomorphic bias outlined in the human–human interaction script. These studies add support to the following hypothesis offered:

H3: A human will be perceived as more socially attractive than a robot.

H4: A human will be perceived as more task attractive than a robot.

Similarly, source credibility (McCroskey & Teven, 1999), made up of perceptions of one's competence (expertise; or does someone know about something); trustworthiness (character and honesty; or can I trust that someone to be honest about that something), and goodwill (a perception of caring, or does that someone have my interests in mind) may also work similarly as evident in several studies (C. Edwards et al., 2021; Finkel & Krämer, 2022). This may be especially true for the goodwill aspect of credibility, as it is more social perception and could be primed by the presence of anthropomorphic cues. As noted in the Spence et al. (2021) study, perceptions of source credibility were highest with the professional meteorologist, followed by the amateur meteorologist, and the lowest levels of perceived source credibility emerged in the condition with the weather social robot. The authors note that all three dimensions of credibility (competence, trust, and goodwill) followed the same pattern.

However, even without the presence of an anthropomorphic cue, similar results have emerged. Research by Kim et al. (2022) examined a radio AI newscaster and a radio human newscaster in a broadcast concerning severe weather. There were higher perceptions of credibility for the human newscaster compared to the AI newscast. Thus, preferences for humans may not be the result of only a visual prime, but any prime concerning the humanness of the communicator. Given that credibility may be a more social perception and the previous study found differences between a human and robot in these perceptions the following hypothesis is offered:

H5: A human will be perceived as more credible (competence, trustworthiness, and goodwill) than a robot.

The look of a social actor is one that likely plays a part in our responses to that actor. However, it is not the only one. Evidence suggests that even if we "know" that something does not warrant a human/social response, we still may respond to that entity with one. The Computers are Social Actors paradigm (CASA; Nass & Moon, 2000; Nass et al., 1994; Reeves & Nass, 1996) is the basis of this position. This paradigm suggests that when a technology triggers a social response, we respond socially, especially if it stems from an overlearned heuristic (Nass & Moon, 2000). Thus, if a robot does something to trigger a heuristic of social action, we may be more likely to respond as we do to other social actors (i.e., humans).

The CASA paradigm suggests that interpersonal communication theory and research are relevant for considering AI and social robots (Spence et al., 2023; Westerman et al., 2020). Among humans, social relationships often begin and grow through self-disclosure, as this is how a social actor reveals themself to another entity or social actor. One simple self-disclosure that individuates an actor and may begin the social process is providing one's name. Indeed, naming is a powerful speech act, as argued by Palsson (2014), and serves as a "technology of belonging." Names impact people's impressions of the person as well (e.g., Young et al., 1993).

Presenting a self is what the goal of a social bot is, so it can present itself as being like another social actor, and thus, a relationship can be formed (Gehl & Bakardjieva, 2017). Social robots have been found to be preferred individually compared to in groups (Fraune et al., 2015), again suggesting that people want such bots to present more of a self. Fritz (2018) explained that having a human name rhetorically situates a robot to be interpellated as a subject, and connotes the uniqueness and "hailability" of a person or pet. Indeed, machines with names (as part of a variety of things) seem to be more anthropomorphized, whether it be autonomous vehicles (Waytz et al., 2014) or chatbots (Araujo, 2018), as well as increasing other social responses. Robots that have a name also seem to trigger more human/social responses to them (Darling, 2017). Given the general finding here that naming tends to be a socializing cue, the following hypotheses are offered:

H6: A social actor that provides a name will be perceived as more human than one that does not.

H7: A social actor that provides a name will be perceived as having more electronic propinquity than one that does not.

H8: A social actor that provides a name will be perceived as more socially attractive than one that does not.

As stated above, research on ingroups vs. outgroups have shown that "others" are often stereotyped negatively as cold and incompetent (Lee & Fiske, 2006). If providing a name within an introduction makes a social actor, such as a robot, be perceived as more similar to a person than if no name is provided, then this may lead to more positive impressions. Moreover, the act of providing a name may reduce perceived anonymity and cause a more favorable impression. Research has shown that individuals perceive higher levels of source credibility of risk information when the identity of the source is known (Lin et al., 2016). Other research has shown that the absence of individual identifications in various situations, such as voice changers, pseudonyms, and nicknames, have the ability to impact perceptions (Graf et al., 2017; Lin et al., 2019). Given these past findings, the following hypotheses are offered:

H9: A social actor that provides a name will be perceived as more task attractive than one that does not.

H10: A social actor that provides a name will be perceived as more credible (competence, trustworthiness, and goodwill) than one that does not.

It is not clear if/how these two pieces of information about a social actor would interact to impact these social and task related perceptions. Thus, a general research question (RQ) asks if there are interaction effects on any of these perceptions.

Method

Overview

A 2 (ontological frame; robot vs. human) × 2 (name; provided or not) between-subjects experiment was conducted to test the hypotheses offered in this study (and to test for possible interaction effects between the two independent variables). Participants were asked to log into a website, where, after providing informed consent, they were welcomed to the study by watching a video of either a robot or a human "host" for the study. This host either said their name as part of the greeting or not. These conditions were fully crossed and randomly assigned to participants, leading to four different conditions: human host that gave a name (n = 77), human host that did not give a name (n = 80), robot host that gave a name (n = 72), and a robot host that did not give a name (n = 77). After the greeting, participants were asked to respond to several measures about this greeter and then told the study was over.

Participants

Data were collected from 332 participants recruited from an introductory communication course at a public university in the upper Midwestern United States. The removal of 20 participants that responded "yes" to a question asking if they recognized the host (7 in human host condition, 13 in robot host conditions) and six participants who failed to complete measures left data from 306 for analysis. One-hundred and forty-eight participants self-identified as male (48.4%), 147 (48.0%) as female, 2 (0.7%) as women, 3 (1.0%) as nonbinary, 1 (0.3%) as agender, with 5 (1.6%) not responding. The majority of participants self-identified as White/Caucasian (n = 263, 85.9%). Participants' ages ranged from 18 to 41 years (M = 18.93, SD = 2.15). A sensitivity power analysis was conducted using G*Power 3.1 (Faul et al., 2007), which suggested this sample size had 80% power for detecting effects with a Cohen's f of .16 at the .05 level, which is a relatively small effect size.

Stimulus Materials

Four different videos were created for this study; one for each of the four conditions. The videos can be seen at the following link: https://osf.io/y62ak/. There was one video for each of the human conditions. In these human conditions, a Caucasian, middle-aged looking and sounding male introduced the study. The specific male was chosen because, although he was a graduate student at the university where the data was collected at the time of data collection, he was not a teaching assistant, and therefore, combined with the fact that he was older than most students, it was considered less likely that students in the class that participants were recruited from would recognize him. The male was recorded from the waist up with a plain wall as the background. In condition A, the video consisted of the introduction to the research study in which a human male provided that introduction. The human male did not use a name in the introduction. It was 11 seconds in length and recorded in 720p HD with a frame height of 720 and width of 1280. The video both had a fade-in and fade-to-black. In condition B, the video format features were identical except that the name "Mike" was used by the human male in the introduction and the video was 12 seconds in length. There was also one video for each of the robot conditions. In these robot conditions, the angle and the background were the same as in the human conditions, with the "host" being recorded from the "waist" up to the head in the same room as the human conditions; however, the experimental manipulation differed in that a robot delivered the script. The robot in the video was an Ohmni® Telepresence Robot with a graphic screen that projected a human-like face based on the MAKI Humanoid robot. This robot has been used in other studies (see Edwards et al., 2016; Michaelis & Mutlu, 2019; Rainear et al., 2021). In condition C, the script and video features were identical to condition A. The length of the video was 13 seconds. In condition D, the script and video features were identical to condition B; however, the experimental manipulation differed in that a robot delivered the script. The video was 14 seconds long. The voice for conditions C and D were taken from the audio files of videos A and B and then modified with the program Audacity to emulate a synthetic voice.

Measures

Perceived Humanness

After viewing one of the four videos (randomly assigned), participants responded to measures about the "host" they saw in the video. The first of these was a measure of perceived humanness, adapted from Bartneck et al. (2009), and previously used by Author. Using a five-point response set, this adaptation contained four semantic differential items (e.g., "machinelike-humanlike"). The scale had acceptable reliability (α = .91). Scores on this index ranged from 1 to 5, with a mean of 2.91 (SD = 1.23).

Electronic Propinquity

Electronic propinquity was measured using Walther and Bazarova's (2008) scale. Using a seven-point response set, this measure consists of five semantic differential items (e.g., "disconnected-connected"). Scores on individual items were recoded so that higher scores on the index meant greater electronic propinquity. The scale had acceptable reliability (α = .86). Scores on this index ranged from 1 to 7, with a mean of 3.78 (SD = 1.23).

Task Attraction

Task attraction was measured using a version of McCroskey and McCain's (1974) measure. Task attraction consisted of five items (e.g., "I couldn't get anything accomplished with them") using a seven-point response set. Scores on individual items were recoded so that higher scores on the index meant greater task attraction. The scale had acceptable reliability (α = .73). Scores on this index ranged from 1 to 7, with a mean of 4.68 (SD = 1.06).

Social Attraction

Social attraction was measured using a version of McCroskey and McCain's (1974) measure. Social attraction consisted of six items (e.g., "They just wouldn't fit into my circle of friends.") with a seven-point response set. Scores on individual items were recoded so that higher scores on the index meant greater social attraction. The scale had acceptable reliability (α = .87). Scores on this index ranged from 1 to 6.5, with a mean of 3.90 (SD = 1.15).

Source Credibility

Source credibility was measured using a version of McCroskey and Teven's (1999) measure. There are three different types of credibility measured using this scale: competence, trustworthiness, and goodwill. One item ("bright-stupid") was removed from the original competence measure, leaving five semantic differential items (e.g., "informed-uninformed") with a seven-point response set used for analysis. Scores on individual items were recoded so that higher scores on the index meant greater competence. The scale had acceptable reliability ($\alpha = .84$). Scores on this index ranged from 1 to 7, with a mean of 5.11 ($SD = 1.12$). Trustworthiness consisted of six semantic differential items (e.g., "honest-dishonest") with a seven-point response set. Scores on individual items were recoded so that higher scores on the index meant greater trustworthiness. The scale had acceptable reliability ($\alpha = .86$). Scores on this index ranged from 1 to 7, with a mean of 4.68 ($SD = 1.11$). Goodwill consisted of six semantic differential items (e.g., "has my interests at heart–doesn't have my interests at heart") with a seven-point response set. Scores on individual items were recoded so that higher scores on the index meant greater goodwill. The scale had acceptable reliability ($\alpha = .83$). Scores on this index ranged from 1 to 7, with a mean of 3.90 ($SD = 1.17$). Please see Table 1 for overall descriptive statistics and correlations for each measured variable.

TABLE 1 Descriptive Statistics and Correlations for Study Outcome Variables

Variable	α	*M*	*SD*	1	2	3	4	5	6	7
1. Perceived Humanness	.91	2.91	1.23							
2. Electronic Propinquity	.86	3.78	1.23	.26**						
3. Task Attraction	.73	4.68	1.06	.52**	.23**					
4. Social Attraction	.87	3.90	1.15	.61**	.38**	.54**				
5. Competence	.84	5.11	1.12	.34**	.11	.57**	.22**			
6. Trustworthiness	.86	4.68	1.11	.60**	.23**	.59**	.48**	.69**		
7. Goodwill	.83	3.90	1.17	.74**	.43**	.53**	.67**	.33**	.64**	

Note. $*p < .05$, $**P < .01$

Results

In order to test the hypotheses and research question offered in this study, a series of 2 × 2 Analyses of Variance (ANOVAs) were conducted for each dependent variable, with frame (human vs. robot) and name (did so or not) as the independent variables. In general, frame (whether the host was human or a robot) had a significant main effect on each dependent variable. Whether the host named themself or not in the video had no significant main effect on any dependent variable, and there were no significant interaction effects for any variable. More details are included below. Please see Table 2 for descriptive statistics across condition, and Tables 3–9 for ANOVA details for each outcome variable.

TABLE 2 Outcome Measure Means, Standard Deviations, and *N* Across Conditions

	Robot		Human	
	Name	No name	Name	No name
Perceived Humanness	1.98 (.84) *n* = 72	2.12 (1.03) *n* = 76	3.70 (.90) *n* = 74	3.77 (.79) *n* = 80
Electronic Propinquity	3.58 (1.35) *n* = 70	3.68 (1.09) *n* = 77	3.82 (1.22) *n* = 77	4.01 (1.24) *n* = 78
Task Attraction	4.06 (1.07) *n* = 72	4.32 (1.12) *n* = 77	5.12 (.84) *n* = 77	5.16 (.75) *n* = 80
Social Attraction	3.23 (1.16) *n* = 72	3.53 (1.29) *n* = 76	4.31 (.87) *n* = 76	4.46 (.73) *n* = 79
Competence	4.66 (1.30) *n* = 71	4.87 (1.07) *n* = 76	5.39 (1.03) *n* = 76	5.49 (.89) *n* = 79
Trustworthiness	4.10 (1.08) *n* = 70	4.20 (1.05) *n* = 77	5.17 (.90) *n* = 77	5.17 (.93) *n* = 79
Goodwill	3.22 (1.10) 72	3.31 (1.21) 76	4.38 (.85) 77	4.61 (.80) 79

TABLE 3 ANOVA for Perceived Humanness

	df	*F*	*p*	η^2
Frame	1	266.00	< .001	.47
Name	1	1.09	.297	.00
Interaction	1	.11	.736	.00

TABLE 4 ANOVA for Electronic Propinquity

	df	*F*	*p*	η^2
Frame	1	4.09	.044	.01
Name	1	1.09	.296	.00
Interaction	1	.10	.753	.00

TABLE 5 ANOVA for Task Attraction

	df	*F*	*p*	η^2
Frame	1	75.99	< .001	.20
Name	1	1.87	.173	.00
Interaction	1	1.08	.300	.00

TABLE 6 ANOVA for Social Attraction

	df	*F*	*p*	η^2
Frame	1	72.01	< .001	.19
Name	1	3.84	.058	.01
Interaction	1	.44	.507	.00

TABLE 7 ANOVA for Competence

	df	*F*	*p*	η^2
Frame	1	29.38	< .001	.09
Name	1	1.58	.210	.00
Interaction	1	.21	.650	.00

TABLE 8 ANOVA for Trustworthiness

	df	*F*	*p*	η^2
Frame	1	80.32	< .001	.21
Name	1	.20	.656	.00
Interaction	1	.20	.656	.00

TABLE 9 ANOVA for Goodwill

	df	*F*	*p*	η^2
Frame	1	114.91	< .001	.28
Name	1	1.89	.171	.00
Interaction	1	.40	.525	.00

To test H1 and H6, which predicted that human framing of the study host and the host providing a name would lead to greater perceptions of humanness, a 2 × 2 ANOVA was conducted on perceived humanness. Frame had a significant main effect on perceived humanness [$F(1, 298) = 265.99$, $p < .001$, $\eta^2 = .47$] such that the human host ($M = 3.73$, $SD = .84$) was seen as more human than the robot one ($M = 2.05$, $SD = .94$). Thus, data were consistent with H1. There was no significant main effect of name on perceived humanness [$F(1, 298) = 1.09$, $p = .297$], thus data were not consistent with H6. There was also no significant interaction effect between frame and name [$F(1, 298) = .11$, $p = .736$].

To test H2 and H7, which predicted that human framing of the study host and the host providing a name would lead to greater perceptions of electronic propinquity with that host, a 2 × 2 ANOVA was conducted on electronic propinquity. Frame had a significant main effect on electronic propinquity [$F(1, 298) = 4.09$, $p = .044$, $\eta^2 = .01$] such that participants perceived more electronic propinquity with the human host ($M = 3.92$, $SD = 1.23$) than the robot one ($M = 3.63$, $SD = 1.22$). Thus, the data were consistent with H2. There was no significant main effect of name on electronic propinquity [$F(1. 298) = 1.09$, $p = .296$], data were not consistent with H7. There was no significant interaction effect between name and frame [$F(1, 298) = .10$, $p = .753$].

To test H3 and H8, which predicted that human framing of the study host and the host providing a name would lead to greater social attractiveness of the host, a 2 × 2 ANOVA was conducted on social attraction. Frame had a significant main effect on social attraction [$F(1, 299) = 72.01$, $p < .001$, $\eta^2 = .19$] such that participants perceived the human host as more socially attractive ($M = 4.39$, $SD = .80$) than the robot one ($M = 3.38$, $SD = 1.23$). Thus, the data were consistent with H3. There was no significant main effect of name on social attraction [$F(1, 299) = 3.61$, $p = .058$]; thus, the data were not consistent with H8. There was no significant interaction effect [$F(1, 299) = .44$, $p = .507$].

To test H4 and H9, predicting that human framing of the study host and the host providing a name would lead to greater task attractiveness of the host, a 2 × 2 ANOVA was conducted on task attraction. Frame had a significant main effect on task attraction [$F(1, 302) = 75.99$, $p < .001$, $\eta^2 = .20$] such that participants perceived the human host as more task attractive ($M = 5.14$, $SD = .80$) than the robot one ($M = 4.19$, $SD = 1.10$). Thus, the data were consistent with H4. There was no significant main effect of name on task attraction [$F(1, 302) = 1.87$, $p = .173$], and so the data were not consistent with H9. No significant interaction effect [$F(1, 302) = 1.08$, $p = .300$] was found.

Finally, to test H5 and H10, predicting that human framing of the study host and the host providing a name would lead to greater perceived credibility of the host, a 2 × 2 ANOVA was conducted on each of the three subcomponents of credibility. Frame had a significant main effect on competence [$F(1, 298) = 29.38$, $p < .001$, $\eta^2 = .09$] such that participants perceived the human host as more competent ($M = 5.44$, $SD = .96$) than the robot one ($M = 4.77$, $SD = 1.19$). Frame also had a significant main effect on trustworthiness [$F(1, 299) = 80.32$, $p < .001$, $\eta^2 = .21$] such that participants perceived the human host as more trustworthy ($M = 5.17$, $SD = .91$) than the robot one ($M = 4.15$, $SD = 1.06$). Frame also had a significant main effect on goodwill [$F(1, 300) = 114.91$, $p < .001$, $\eta^2 = .28$] with participants seeing more goodwill from the human host ($M = 4.50$, $SD = .83$) than the robot one ($M = 3.27$, $SD = 1.16$). Thus, the data were consistent with H5. There was no significant main effect of name on perceived competence [$F(1, 298) = 1.58$, $p = .210$], trustworthiness [$F(1, 299) = .20$, $p = .656$], nor goodwill [$F(1, 300) = 1.89$, $p = .171$]. Thus, the data were not consistent with H10. No significant interaction effects were found for competence [$F(1, 298) = .21$, $p = .650$], trustworthiness [$F(1, 299) = .20$, $p = .656$], nor goodwill [$F(1, 300) = .40$, $p = .525$].

Discussion

The current study was designed to examine the role that ontological frame (robot vs. human) and name (naming or not) of a social actor had on various perceptions of that actor. In general, the frame had significant effects on all dependent variables, such that the human host was seen as more human, electronically propinquitous, socially and task attractive, and all three components of credibility measured (competence, trustworthiness, and goodwill) than the robot host. Whether the host named themself or not did not have significant effects on any of these perceptions, and there were also no interaction effects between frame and name. These results are discussed in more detail below.

First, consistent with hypotheses, a video of a human host introducing a study was perceived more positively overall than a robot one. This is very much in line with the human-human interaction script found in previous research (Craig & Edwards, 2021; Edwards et al., 2019; Edwards et al., 2016; Spence et al., 2014), suggesting that people expect to interact with humans when they know they are going to interact with a social actor. The current study suggests this script may also apply to other expectations of experiences with social actors as well, including the role of study *host*, introducing what people will be doing, as used here. Thus, perhaps the biggest practical application of the findings in this study are that humans may make for better greeters than robots overall, at least for the kind of one-time, noninteractive greeting examined in the current study, as the human-host conditions were perceived more positively overall as compared to the robot-host conditions. This might be especially important for some of the larger effects found in the current study, which cut across both work and social outcomes. For example, some of the stronger effects were found on task attraction ($\eta^2 = .20$) and trustworthiness ($\eta^2 = .21$), with the human host perceived as more task attractive and trustworthy than the robot host. This was also true for social attraction ($\eta^2 = .19$) and goodwill ($\eta^2 = .28$), with the human host perceived as higher on both of these than the robot host. Thus, it would seem that people engaging with this kind of *hosting* video both like and trust it more when a human is the one talking to them. Companies may want to consider being very careful about using a robot for this purpose, unless there is good reason to do so.

As mentioned above, although there were significant differences found for ontological frame on each variable of interest in this study, there was variance in the effect sizes. For example, although statistically significant, the effect size on electronic propinquity was relatively small ($\eta^2 = .01$). Thus, although this result was in the same pattern as those found for other outcome variables measured, the effect size was smaller than those found for other outcomes. Perhaps one reason that this effect size was much smaller than the others was the specific person that was used for the human host video. In order to try to make sure that participants would not be familiar with the human appearing in the video, a particular person was chosen. This person was a middle-aged man, who appears and sounds middle-aged. Given the use of a middle-aged male actor, it could be expected that our human host may have prompted *out-group* responses from the relatively young sample (Cohen et al., 2019), and thus, relatively low increases in perceived closeness central to electronic propinquity, compared to other outcomes measured. Future research can be conducted to test for possibilities of different patterns of relative effect sizes using different humans (and robots, for that matter) as comparisons.

Perhaps robots are also less alien to people now than they may have been in the past. Greater familiarity with robots may bring them closer to humans in electronic propinquity. It is also possible that greater familiarity with robots here means people have developed scripts for dealing with technology (Gambino et al., 2020), and this may lead people to have somewhat similar responses to technology although those responses might be driven by different processes (Edwards & Edwards, 2022). Future research is necessary to consider these possibilities.

However, whether the social actor told participants their name or not during this introduction had no impact on participants' perceptions of said actor's humanness, electronic propinquity with the actor, social and task attraction toward the actor, or credibility of the actor. This was surprising, as previous research provided reasons to assume that naming can be a cue that individuates an actor (e.g., Darling, 2017; Fritz, 2018), which would make the actor more social and more like the participant. Interestingly, in some of the past studies showing that name and an impact on anthropomorphism and other outcomes, name was manipulated along with other anthropomorphic cues. For example, Waytz et al. (2014) used three different car conditions in their study: A *normal* one, where people drove a car themselves, an *agentic* one, where the vehicle was able to control steering and speed, and an *anthropomorphic* condition that added a name, gender, and human voice to the car. Similarly, Araujo (2018) differentiated an anthropomorphic agent from a non-anthropomorphic agent by giving the anthropomorphic agent a human name (instead of a nonhuman one), as well as having the agent interact using less formal language and asking the participant to use more human dialogical cues to start and end the interaction. These studies did not explicitly test which of these individual cues would lead to anthropomorphism specifically, but the current research seems to suggest that name alone may not always be enough of an anthropomorphic cue to increase perceived humanness of a machine. Perhaps naming operates as what Lombard and Xu (2021) refer to as a secondary social cue in this situation; one that is neither sufficient nor necessary to lead to the social outcomes examined in the context of the current research. Future research can examine this possibility.

Perhaps an explanation for this pattern of findings is this: The visual/nonverbal information that clearly showed the social actor to be human or robot was such a strong initial piece of information about the social actor that it overrode any initial perception that the naming could have caused, especially given the way that name was manipulated in the current study. Perhaps providing more reminders of the host's name (e.g., visually representing it on the screen as well as having the host say it) would make it more salient even with the seemingly stronger attention paid to the ontological frame. It is also possible that the presence of a name (or not) would have been a more important piece of information if participants were led to believe that further and actual interaction with the social actor was going to take place. For example, anticipation of future interaction has been found to matter in research on social information processing theory (SIPT; Walther, 1992), such that such anticipation may be important for people to be willing and able to pay attention to information like this (Kellerman & Reynolds, 1990; Walther, 1994). In other words, people need motivation to do things that help form impressions of other social actors, but can do so with such motivation. Perhaps the ontological frame was too great a cue to ignore, but participants felt no particular need to attend to something like a name here without a motivation such as anticipating future interaction, and host names may be more salient for participants who expect future interactions. Although this does not change the fact that the name manipulation used did not seem to matter in the static, initial impression environment of the current study, it may help explain why not, and why we may still expect naming to matter in future studies (and other studies that did show the importance of name). This is something that future research can examine.

Given this possibility, it is also possible that moving past initial impressions and actually interacting with the social actor may make the naming a more important piece of information. Again, Walther's (1992) SIPT suggests that impressions can be formed through interaction in CMC, and has been argued to be applicable to the study of human-machine communication (HMC; Westerman et al., 2020). This has also been seen in previous studies on the human-human interaction script. Studies found that although initial impressions (based on expectations) of interacting with robots were lower than with humans (Edwards et al., 2019; Edwards et al., 2016; Spence et al., 2014); however, after actually interacting for 5 minutes, these differences largely disappear, and may even turn to more positive impressions with robots (Edwards et al., 2019). Furthermore, Gockley et al. (2005) found that a robot serving as a receptionist was able to build relationships with recurring visitors, so such interaction and relationship building processes have shown to be possible in a similar setting. Perhaps providing a name could kickstart later actual interactions, as other information may (Westerman et al., 2008), changing the nature of the interaction itself, and leading to predicted differences in the types of perceptual outcomes measured in the current study. Again, future research could examine this in a situation involving actual interactions with various social actors (e.g., humans and robots) that provide names or not.

Considering interactions with social actors, it is also possible that how a social actor's name is used matters in potential interactions as well. Fritz (2018) suggested that the real power of naming robots is not only in the name itself, but in the fact that the person interacting with said robot has to address them by that name (engaging human, or even pet, scripts). The robot then also responds to that name, either verbally or nonverbally, such as by turning to look at the person who has addressed them. If this is the case, then actually having an interaction with a robot would be important for seeing the kinds of differences that were predicted due to naming in this study. It is also possible that hearing another person use the robot's name in addressing the robot (rather than addressing it oneself) would also work to humanize the robot more and perhaps lead to other human perceptions, as expected. For example, Darling (2017) had other people use a robot's name when addressing it. Future research can examine the possibility of activating human interaction scripts and processes based on these kinds of hailing of a robot by name within an interaction, even when the initial use of the name is a relatively small cue.

Author Biographies

David Westerman (PhD, Michigan State University) is an Associate Professor in the Department of Communication at North Dakota State University. His research and classes focus on how people communicate through and with technology, especially focusing on how we perceive social actors of both the human and machine variety. He is the Director of the Department of Communication's Social Robotics Lab at NDSU, and affiliated with the Communication and Social Robotics Lab (www.combotlabs.org).

https://orcid.org/0000-0001-9550-0304

Michael Vosburg (PhD, North Dakota State University) is an Assistant Professor of Mass Communication at Benedict College. He had a 33-year career in photojournalism, and managed visual departments for 25 years at *The Missourian* (Columbia), *The San Angelo (TX) Standard-Times*, and *The Forum of Fargo-Moorhead* (ND-MN). He champions using mobile devices to speed the delivery of high-quality photographs to readers in minutes. His primary research interest is media effects of photographs, a subject he also theorizes.

https://orcid.org/0000-0001-8613-7670

Xinyue "Gordon" Liu (MA, Boston University) is a Doctoral Candidate in the Department of Communication at North Dakota State University, where he also currently serves as the Assistant Basic Course Director. His primary research focus centers on how technology can be used in the classroom, especially to help improve performance in the basic course.

Patric R. Spence (PhD, Wayne State University) is a Professor at University of Central Florida. His primary areas of research are crisis communication and social robotics. He is affiliated with the Communication and Social Robotics Labs (www.combotlabs.org).

https://orcid.org/0000-0002-1793-6871

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HUMAN-MACHINE

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