Empathetic engagement drives nonverbal interactions between humans and a small-scale robot

Jude Fogarty[1], Ifeoma Nwogu[2], and Ryan St. Pierre[2,3]

***Abstract*— Recent work in Human-Robot Interaction (HRI) has called for a reexamination of the assumptions underlying human-centered frameworks of interaction and social acceptability. Rethinking human-centered models of sociality is particularly important for understanding empathy and affective responsiveness, as it enables us to imagine alternative modes of connection beyond the human. In this study, we designed a minimalist, non-humanoid tiny robot capable of displaying a limited set of affective expressions in response to non-verbal, tactile interactions, and tested the effectiveness of the robot's design through an open-ended, qualitative study. Our findings indicate that minimal emotional expression – even at small scales and in non-humanoid design – can prompt empathy, attentiveness, and responsiveness in human-robot interactions.**

I. INTRODUCTION

Research on social acceptability and effective social robot design has tended to focus on human resemblance, both in morphology and in interactional patterns [1], [2], [3]. Yet as robots increasingly populate diverse parts of our world, it is important to understand how robots are perceived, understood, and accepted across scales, morphologies, and forms of interaction. Recent work in Human-Robot Interaction (HRI) has called for a reexamination of the assumptions underlying these human-centered frameworks [4], [5], [6], [2], particularly given that research has shown humans identify with robots across contexts, uses, and forms, not just with social robots in social contexts [7], [3].

Rethinking human-centered models of sociality is particularly important for understanding how and why empathy and identification are elicited between humans and robots. For example, human participants interacting with a commercially available, non-humanoid companion robot, Cozmo, sought to understand why the robot was sad, and how they could ameliorate any potential negative interactions to make the robot happy again [8]. Even in a virtual environment featuring drones with expressive faces, participants extended empathy toward the drone, and expressed wanting to give it a hug. While part of this identification is explained by the human tendency to anthropomorphize, anthropomorphism itself does not happen consistently across contexts [7], and anthropomorphic embodiments are not universally more effective than zoomorphic or mechanical embodiments [1], [9].

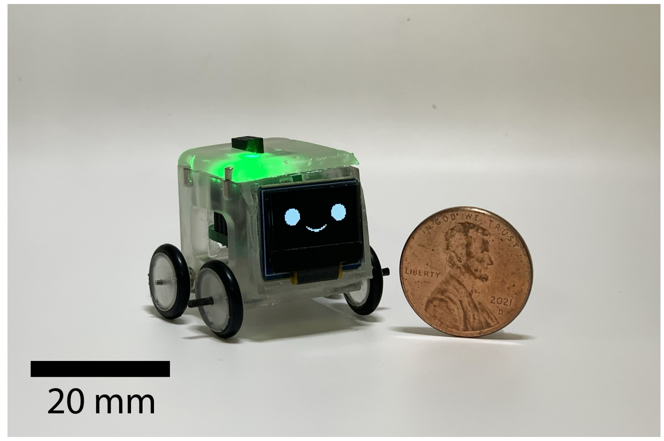

Fig. 1: The interactive tiny robot, pictured next to a US penny, is approximately 1 cubic inch in volume ($25\,\mathrm{mm} \times 26\,\mathrm{mm} \times 24\,\mathrm{mm}$) with a mass of $10.8\,\mathrm{g}$. The robot has onboard sensing and computation to display affect in response to interaction.

Furthermore, situating HRI in purely human or anthropomorphic terms constrains design innovations and the possibilities we can imagine for social interactions between humans and embodied artificial agents [2], [6], [10], [4]. It is necessary, therefore, to move beyond relying on human physical and social characteristics, yet such a project first requires a critical evaluation of our foundational assumptions about effective social design and a remapping of the minimal mitigating factors encouraging empathetic identification between humans and robots.

As Ringe et al. [11] have recently argued, HRI needs a more rigorous system of design feature classification beyond the loose categories of anthropomorphic, zoomorphic, and mechanical. Studies seeking to categorize robot features, including Ringe et al., tend to rely on images or video of existing robots [11], [1]. While this approach is expedient for analyzing large datasets, it cannot capture the full effects of embodied design. The long-term project from which the pilot study described in this paper is drawn intervenes in this gap and contributes to ongoing understandings of design categorization and reception through using real, embodied robots and adopting a user-centered, iterative process of design and testing, in which ongoing analysis of user experience shapes design decisions.

As a first step, we designed a minimalist, non-humanoid

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[1]Department of Engineering Education, University at Buffalo, Buffalo, NY 14260, USA

[2]Department of Computer Science and Engineering, University at Buffalo, Buffalo, NY 14260, USA

[3]Department of Mechanical and Aerospace Engineering, University at Buffalo, Buffalo, NY 14260, USA

{hrfogart, inwogu, ryans}@buffalo.edu

tiny robot (Fig. 1) capable of displaying a limited set of affective expressions in response to participant touching and handling. As Urakami and Seaborn [3] argue, basic design elements (e.g. size, shape, form, texture, color) have the capacity to shape affective engagement, as even these details are communicative. We thus consciously limited the embodied and expressive design features of our robot and observed interactions through an open-ended study protocol that enabled us to gain insights into processes of identification and empathetic response in human-robot interactions.

II. Robot design

In this section, the robot design is briefly outlined to detail its explicit hardware and software capabilities. The robot itself has a small form factor, occupying a volume of $25\,\mathrm{mm} \times 26\,\mathrm{mm} \times 24\,\mathrm{mm}$ with a mass of $10.8\,\mathrm{g}$. This small-scale design constrains the hardware available to be integrated, but this constraint is purposeful, as it enables us to focus on the key design features enabling emotional recognition. At the same time, the unintimidating, small-scale embodiment of the robot invites tactile interaction between a human and the robot.

The electrical hardware of the robot consists of two custom-printed circuit boards (PCBs) that are stacked to ensure electrical and mechanical connections. The base board consists of a RISC-based microcontroller with $4\,\mathrm{kB}$ flash memory (ATtiny44, Atmel) which controls a small $0.49\,\mathrm{in}$ ($64\,\mathrm{px} \times 32\,\mathrm{px}$) monochrome OLED display. The second custom PCB consists of electronics for inertial measurements (MPU-6050, TDK InvenSense). Finally, the PCBs are connected to a $3.7\,\mathrm{V}$ $30\,\mathrm{mA\,h}$ LiPo battery through a voltage regulator (TPS7A0533PDBZR, Texas Instruments) to provide stable power to the robot.

The body of the robot and four wheels were 3D printed using an SLA 3D printer (FormLabs Form 3+). Wheels were friction fit to each of the motors, though the robot did not move in this study, as the driving sets and passive wheels were attached to the chassis with a carbon fiber rod axle. $7\,\mathrm{mm}$ diameter by $2\,\mathrm{mm}$ thick o-rings were wrapped around each wheel as a tire. A photograph of the final assembled robot is shown in Figure 1.

A. Expressive software design

Four different expressive faces, along with a neutral face, were designed for the robot. These faces were based on Ekman's universal facial expressions [12]: happy, sad, angry, and surprised. Since our goal was simplicity, we chose not to include Ekman's other two expressions – fear and disgust – which tend to be more complex. We further included a neutral face to serve as a baseline and transition point. Recent studies of a simulated drone with similar categorical emotional states of varying intensities observed that humans based their interpretations of the facial expression on category over intensity [13]. This suggests we can minimize the number of emotional displays to simple categories without sacrificing effective expressiveness.

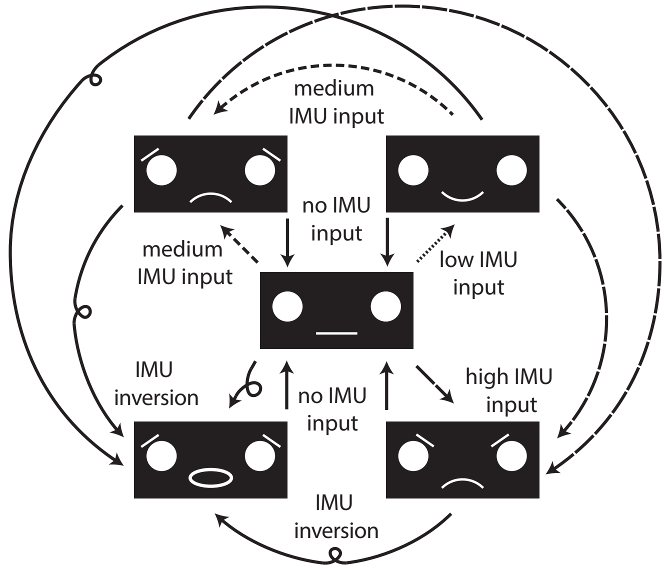

Fig. 2: A software finite state machine utilizes sensory feedback from an on-board IMU to display faces as a user interacts with the robot.

A software finite state machine was designed to display a static face given a sensed inertial state with the robot, shown graphically in Figure 2. When a user is not interacting with the robot, i.e., measurements are not beyond the noise level, the robot displays a neutral face. The robot will then display a happy, sad, or angry face based upon the sensed accelerations of the IMU. If the robot is inverted, it will display a surprised face. The robot can transition between emotive faces based upon increasing interaction, and can be reset to a neutral state if left alone.

III. Methodology

A. Study design

The aim of this study was to observe the effectiveness of the robot design for eliciting empathetic responses over the course of nonverbal, tactile interactions. A prior study [14] confirmed that human participants were able to recognize the designed robot faces. In that study, participants were randomly shown the five facial expressions (neutral, happy, sad, angry, and surprised) and were asked to name them as they appeared, with all participants correctly identifying the expressions. Therefore, this study focused solely on the interactions between the humans and robot.

Our goal in observing these interactions was to understand how participants were perceiving and making sense of the robot. In line with Yolgormez and Thibodeau's [2] assertion of the valuable insights to be gained when research outcomes are not strictly delimited, we adopted a loose, inductive study design [15] so as to not limit the range of potential responses or impose our own biases on participant perceptions. We provided participants with minimal instructions and minimal limitations on interaction options to enable the broadest possible range of responses.

Each participant was asked to interact with the robot for up to 5 minutes. Participants were told that the study aim was simply to observe how people tend to respond to the robot. They were told they could interact with the robot in any way they wanted – including touching, lifting, speaking, etc. – as long as they did not try to break it, and were instructed to narrate their thought process and observations over the course of the interaction.

Creating open-ended opportunities for participants to narrate and describe rather than answer structured questions can lead to a richer and more authentic dataset [16], [1]. Humans routinely use narrative as a meaning-making tool to impose order, structure, and significance on life events, social relations, and inner experience [17], [18]. Reference to emotional states plays a primary explanatory role in this process, revealing reasoning and motivation and creating cause-and-effect links between events [19]. Prompting participants to narrate their experiences and observations, therefore, enabled us to map how the robot and its expressions were being made sense of and categorized – and how these sense-making activities evolved in response to the robot's changing expressions.

1) Recruitment: This study used a snowball recruitment method [20] where the researchers/authors invited potential participants and asked them to invite others to participate. This process resulted in 11 final participants.

2) Observation and data collection: For validity, a minimum of two out of three researchers were present during all participant interactions and took written notes on the specific ways in which participants interacted with and described the robot. These notes were later cross-referenced during first-cycle coding to identify any potential disparities. At the beginning of each interaction, the researchers provided participants with the instructions described above and then refrained from adding additional context or commentary.

3) Data analysis: Observation notes were analyzed in two coding cycles. In the first cycle, Descriptive and Process Coding [15], [21] were performed separately on all observation notes; they were both generated inductively based on a modified list of questions drawn from Emerson *et al.* [22, p. 177]:

- How do participants talk about, characterize, and understand what is going on? What assumptions are they making? (Descriptive coding)
- What are participants doing? What are they trying to accomplish? What specific means and/or strategies are they using? (Process coding)

In the second coding cycle, Pattern Coding [15] was applied to all Descriptive and Process codes to identify overarching patterns and thematic groups.

IV. Results and Discussion

A. Empathetic engagement

While some participants initially took a distanced approach to the interaction, noting features (or perceived features) and guessing at functionality, all participants either immediately or eventually took on some sense of responsibility for the robot's affective states. In fact, regardless of whether they perceived the robot as a designed object or an emotional interactant, the majority of participants were immediately attuned to the robot's changing expressions. Once they began interaction with the robot through touching or moving, 8 out of 11 participants' first observation was about the robot's affective state, describing how the robot was happy, angry, or sad, or did or didn't like what they were doing.

In vivo coding [21] (i.e. using the the exact language of participants) revealed 21 descriptors for affective states. Significantly, 17 of the descriptors described the robot's emotional state (e.g. happy), while only 4 described the robot's expression (e.g. smiling). This distinction suggests that participants were not solely engaged in expression recognition. Instead, they imaginatively constructed a personality and internal emotional states based on the robot's expression and responsiveness to interaction. This construction of the robot as an object that experiences feelings served as a major driver for most of the participants' non-verbal interactions. Of the 21 affective descriptors, the four most commonly used were "happy" (15 times), "doesn't like" (12), "likes" (11), and "angry" (7). As the opposed terms happy/angry and likes/doesn't like suggest, participants' engagement with the robot primarily centered on identifying how to create positive affective states and avoid negative ones.

B. Nonverbal interaction

Participants' observations of the robot's expressions continued over the course of the interactions. These observations were tied to a desire to understand how their actions were changing the expressions, with participants noting they were "trying to figure" it out (4 participants), that they "want to know what's going on" (1), and that they want to know what makes the robot change or how they can make the robot happy (5). This investment in understanding the robot and making it happy was reflected in the variety of tactile interactions participants engaged in. Process coding revealed 33 separate types of actions, 27 of which were types of non-verbal interactions with the robot. We further organized these non-verbal interaction types into analogous groups, resulting in four representative thematic categories, pictorially represented in Figure 3. These four categories are:

- Pushing and rolling (31 instances)
- Tapping, poking, petting (17)
- Flipping, shaking, rotating, tilting (21 instances)
- Lifting and circling in the air (8 instances)

The wide variety of interactions is representative of the ongoing process of observation and adjustment participants engaged in. As Pelikan et al. [8] have argued, positive affect in robots prompts human interactants to continue performing the same actions, while negative affect prompts interactants to revise their actions. We found this to be true, as typical interactions in our study consisted of participants trying out an action while closely observing the robot's face, noting if a change occurred, what the change was, and adjusting their actions accordingly.

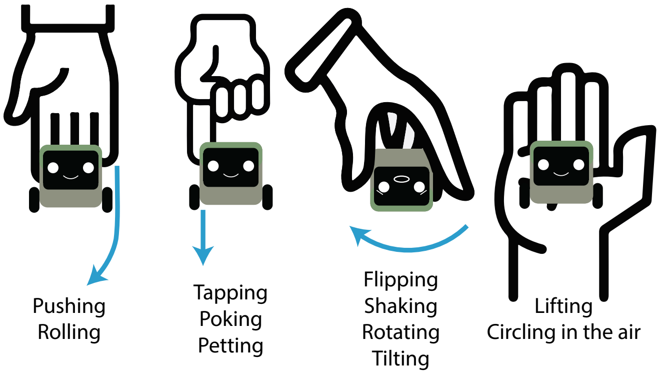

Fig. 3: Depictions of the four representative categories of tactile interaction between a human and the robot, including pushing, tapping, flipping, and lifting. These tactile interactions evoked an affective response by the robot given the expressive software.

For example, one participant immediately began touching and moving the robot according to its changing expressions, flipping it upside down, shaking it, driving it like a car, setting it back down, lifting it in the air, driving it back and forth on the table, lifting it again, having it do a "wheelie," then moving it side to side. Each individual action was accompanied by an observation of what "he" (the robot) likes or doesn't like.

The participant was closely attentive, framing the robot's responses not just in terms of particular interactions, but in terms of timing and intensity, noting for instance, that the robot liked being driven, but only for a short amount of time and that he liked being lifted in the air, but only to "this height specifically." Thus, it was clear that even when participants were driving the robot like a toy car, the robot was driving the interaction.

V. Conclusion and Future Directions

Our qualitative analysis revealed two significant contributions:

1) *Empathetic connection*. Through simple affective displays, we were able to delineate a set of minimal cues that effectively encouraged participants to invest in the robot's perceived emotional states.
2) *Nonverbal, tactile interaction*. The robot's design effectively prompted participants to engage with it through handling and moving, interactions that were shaped by participant observation of the robot's changing expressions.

Overall, these findings indicate that minimal emotional expression – even at small scales and in non-humanoid design – can prompt empathy, attentiveness, and responsiveness in human-robot interactions.

In future research, we plan to develop our questions about the impact of scale and embodiment on human interaction in two key ways. First, we will continue to test minimal design factors by examining how different modalities such as sound and light influence empathetic identification and interactive responses. In addition to establishing foundational design elements, testing these modalities will enable us to identify whether the empathetic engagement we observed in our study was reliant on the visual shorthand for human emotion created by the facial expressions, or whether similar engagement can be elicited through non-humanoid cues. Second, the scale of our robots creates a unique opportunity to study the role of grasping and handling in human-robot interaction, as the size of the robot may encourage certain types of behaviors that might be inhibited at larger scales, where social norms may more strongly affect proxemics and handling. Future research will reproduce the pilot study described in this paper on a larger scale with video recordings to validate our initial findings and to enable close examination of hand gestures and interactions; we will continue this observation of grasps and proxemics across studies of other design modalities as well.

One main limitation of the current study could be the absence of other sensors such as cameras and microphones, to expand the nonverbal interactions with humans. Participants interacting with the robot likely displayed a myriad of facial expressions, but the robot was unable to react to these. Also, in its current state, although the robot could move, movement was not coded into the study protocol, hence a cue like proxemics was not tested as a communication channel.

References

[1] N. Dennler, C. Ruan, J. Hadiwijoyo, B. Chen, S. Nikolaidis, and M. Matarić, "Design metaphors for understanding user expectations of socially interactive robot embodiments," *J. Hum.-Robot Interact.*, vol. 12, Apr. 2023.

[2] C. Yolgormez and J. Thibodeau, "Socially robotic: making useless machines," *AI and Society*, vol. 37, p. 565–578, 2022.

[3] J. Urakami and K. Seaborn, "Nonverbal cues in human–robot interaction: A communication studies perspective," *J. Hum.-Robot Interact.*, vol. 12, Mar. 2023.

[4] K. Zawieska, "The iron cage of social robotics," *J. Hum.-Robot Interact.*, vol. 14, Dec. 2024.

[5] E. S. Cross and R. Ramsey, "Mind meets machine: Towards a cognitive science of human–machine interactions," *Trends in Cognitive Sciences*, vol. 25, no. 3, pp. 200–212, 2021.

[6] M. Sarrica, S. Brondi, and L. Fortunati, "How many facets does a "social robot" have? a review of scientific and popular definitions online," *Information Technology and People*, vol. 33, no. 1, pp. 1–21, 2020.

[7] D. J. Gunkel, *Robot Rights*. MIT Press, 2018.

[8] H. R. Pelikan, M. Broth, and L. Keevallik, ""are you sad, cozmo?" how humans make sense of a home robot's emotion displays," in *Proceedings of the 2020 ACM/IEEE international conference on human-robot interaction*, pp. 461–470, 2020.

[9] W. N. Benson, Z. Anderson, E. Capelle, M. F. Dunlap, B. Dorris, J. L. Gorlewicz, M. Shimizu, and J. B. Weinberg, "Embodied expressive gestures in telerobots: A tale of two users," *ACM Transactions on Human-Robot Interaction*, vol. 12, no. 2, pp. 1–20, 2023.

[10] L. Tripaldi, *Parallel Minds: Discovering the Intelligence of Materials*. Urbanomic, 2022.

[11] R. Ringe, R. Nolte, N. Zargham, R. Porzel, and R. Malaka, "Metamorph – a metamodelling approach for robot morphology," in *Proceedings of the 2025 ACM/IEEE International Conference on Human-Robot Interaction*, HRI '25, p. 627–636, IEEE Press, 2025.

[12] P. Ekman and D. Keltner, "Universal facial expressions of emotion," *California mental health research digest*, vol. 8, no. 4, pp. 151–158, 1970.

[13] V. Herdel, A. Kuzminykh, A. Hildebrandt, and J. R. Cauchard, "Drone in love: Emotional perception of facial expressions on flying robots," in *Proceedings of the 2021 CHI conference on human factors in computing systems*, pp. 1–20, 2021.

[14] Y. Aykanat, J. Fogarty, A. N. Burde, I. Nwogu, and R. St. Pierre, "OSCAR: Open-source companion affective robot," *[in preparation] IEEE Robotics and Automation Letters*.

[15] M. B. Miles, A. M. Huberman, and J. Saldaña, *Qualitative Data Analysis: A Methods Sourcebook*. Sage, 4 ed., 2020.

[16] C. L. Bethel, J. E. Cossitt, Z. Henkel, and K. Baugus, "Qualitative interview techniques for human-robot interactions," in *Human-Robot Interaction: Evaluation Methods and Their Standardization*, pp. 145–174, Springer, 2020.

[17] K. Gergen, "Self-narration in social life," in *Discourse Theory and Practice: A Reader* (M. Wetherell, S. Taylor, and S. J. Yates, eds.), pp. 247–260, Sage, 2012.

[18] P. Ricoeur, *Time and Narrative*, vol. 1. University of Chicago Press, 1984.

[19] D. Edwards, "Emotion," in *Discourse Theory and Practice: A Reader* (M. Wetherell, S. Taylor, and S. J. Yates, eds.), pp. 236–246, Sage, 2012.

[20] K. Leighton, S. Kardong-Edgren, T. Schneidereith, and C. Foisy-Doll, "Using social media and snowball sampling as an alternative recruitment strategy for research," *Clinical simulation in nursing*, vol. 55, pp. 37–42, 2021.

[21] J. Saldaña, *The Coding Manual for Qualitative Researchers*. Sage, 2nd ed., 2013.

[22] R. M. Emerson, R. I. Fretz, and L. L. Shaw, *Writing Ethnographic Fieldnotes*. University of Chicago Press, 2nd ed., 2011.