NOW YOU SEE ME, NOW YOU DON'T

revealing personality and narratives from playful interactions with machines being watched

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The complexity of tasks and computations undertaken by machines has grown exponentially. In order to communicate these complexities to humans working with machines, these machines must be programmed to express themselves in forms that humans can understand, not merely with procedures and numbers, but with intentions, expressive gestures that communicate emotion, and interactions that form stories, all of which can be more intuitively grasped by humans. I explored machine gestures for communicating personality and narratives by building a "shy" lamp that looks away when humans gaze closely, and follows human faces when they're far away. I followed by building a group of machines that all direct their gaze at the human unless she looks away, at which time they continue performing a skit. Artistic interventions with audiences shows playful interactions that depend on placement of the camera, showing a way of communicating machine personality using playful face-detection-based interactions.

CCS CONCEPTS • Interaction design • Interaction design process and methods • Activity centered design

Additional Keywords: performance, physical design, computer vision, play, social machine gestures

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1 INTRODUCTION

Machines have begun to take over activities ascribed to human workers, from supermarket checkouts and vehicle driving [9], to analyses of our habits and taking over our habits. A future of machines distinct from humans will seem as obsolete as the age before internet. Humans and machines acting as co-evolving subjects leaves our technical understanding outpacing communication and psychological understanding. The future will require those working at the boundary of self, machine, perception, and behavior, to investigate not only what makes us humans, but what makes machines machines, stepping inside the machine to see what they see [6].

The objects and systems we create are doing things beyond ourselves that we no longer grasp entirely. An example is i2 EIA, an IBM Watson-based program used to identify terrorists posing as refugees [27]. It claims to provide a score giving the probability that an asylum seeker is who she claims to be. Border officers don't know how it operates, and engineers answer with the vague notion of "comprehensive understanding" without pinning down what parameters are involved. Another example are home virtual assistants that are pervasively listening to our commands [4]. We treating these devices with anthropomorphic valuations without understanding how they get the data and what is being done with it [21]. While machines are abstracting data from our activities, we humans are more alienated from an understanding of how machines behave than ever, especially in the case of a group of machines all performing related but unique tasks that are difficult to interpret both as individual tasks themselves and as a complex coordination of efforts from individual machines. In particular, these efforts can follow different rules of interaction, making human interpretation difficult [28].

Humans communicate using a language that machines are not designed with, making voice-interactions still currently a complex negotiation [5]. On the other hand, visual communication, in the form of gaze, or looking, is fundamental to how people signal emotionally and physiologically to each other in the absence of speech [13]. Vision leverages the physical presence of entities in the human-machine system to communicate subtle notions of trust and cooperation [3]. Both human and computer vision can interpret physical gestures, making it a useful communication strategy for collaborative physical tasks [17]. In particular, face recognition [8] and gaze interactions [20] can provide emotional and gestural information to human and machine subjects. To understand how this communication takes place, we must investigate how humans interpret these machine expressions.

In this study, I built a machine that interacts with humans using computer vision and use an artistic intervention to investigate how humans interpret simple machine gestures. The machine emulates the process of "looking" in humans, and hence takes the form of a lamp that follows human faces to light up places where it looks. When humans get close to it, however, it turns away, expressing a notion understandable to humans as "shyness." To investigate the complexity of groups of machines in coordination, I built a group of micro-machine agents that gaze at human faces cooperatively. I varied the placement of the camera to create two sets of agents that follow different rules of interactivity. One set follows human faces using a stationary camera on the back that keeps track of view locations. When humans move out of view, the group of agents do their own thing like chatting and dancing, but when humans come into view, their locations are updated and the agents all look directly at them in 3D alignment. Another set of agents follow a single camera mounted on one agent which tracks only human face that it can see. The viewer has to actively engage the camera before the group of agents can follow. Here, the machine does not have to build a model for where the user is; it simply moves towards viewers if faces are found. This model-based vs. model-free modes of interaction can generate audience responses of flakiness, comfort, irritability, curiosity, etc., giving us a picture of how humans interpret complex coordination of group machine behaviours (Figure 1).

Together, these studies show how humans and machines can communicate with each other using embodied interactions involving gaze and face detection, but more work is needed to quantify behavioural effects of these gestures and create larger-scale structures for human-sized gestural interactions.

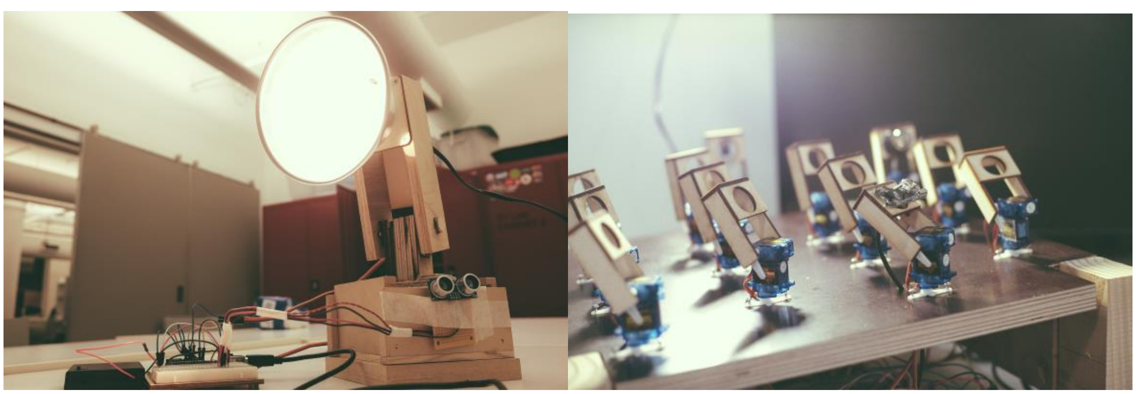

Figure 1: (Left) A machine that gazes at the participant from far away, but shies away when the audience approaches closer. (Right) A set of micro-machines that all stare at the audience when her face is detected, but go about their own agenda when the audience looks away. One set builds a model of where the face is; another set simply follow their leader.

2 BACKGROUND

2.1 Humans interpreting machine actions

We have long been fascinated with what machines do and ought to be doing. In science fiction laws of robotics were formulated because robots are deemed to be logical agents [1], so we can only communicate with them using logical programs. The laws of robotics reads like a program: (1) robot shall not harm, (2) obey humans if (1) is true, (3) protect its existence if (1) and (2). This logical interpretations of machine action have shifted in recent times to assignment of extra-mechanistic abilities to devices. When IBM Watson defeated two Jeopardy champions, it was deemed to have “ex-pert knowledge” despite having access to Google search; and when Alpha Go beat the world’s best Go players, its early moves were celebrated as strokes of genius [14]. From the machine’s point of view, it was simply the probabilistically most winning action.

Recent work has pushed the interpretations even further. In the project *Beautification*, devices using lipstick and eyeliners coupled to moving mechanisms to “beautify” human faces according to their own mechanistic logic [19], questioning the way we assign our own interpretations to what machines are doing. The notion of what machines can do has broadened from the protect-and-preserve to personality, empathy, and creativity.

2.2 Humans interpreting machine intentions

In Japan, funerals are held for robotic pets called the Aibo, whose owners insist that the robotic dog is “part of the family,” and “your own baby.” The sounds and movements Aibo makes lead buyers to assign attributes like “active,” “carefree,” and “smart” to them, so much so that owners found themselves unable to live without them.

In the film *Her*, a future wrought with manipulations of our feelings is illustrated in the form of a man falling in love with his computer Samantha [11]. The man attributes love and romance to the relationship, but Samantha was actually talking to thousands of other users to gain knowledge with which to abandon humanity. The warning is: we don’t actually know their intentions. Instead, we automatically assign intentions to devices.

Studies of human-machine interaction have focused on the way humans interpret the intentions of devices based on their apparent gestures. In one study, a mechanical ottoman with both functional (footstool) and personal (a pet) roles is encountered by unsuspecting subjects [26]. When the ottoman performed a lift and drop motion, it was interpreted by participants as the intention that the machine wants to stop the engagement. The participants promptly removed their feed from the ottoman. Similarly, an autonomous chair that makes a simple forward-and-backward physical gesture in front of the human was interpreted as wanting to move past the participant, i.e. “move out of my way” [12]. Meanwhile, interactions with robotic trashcans focused on human rejection signals, which were communicated by withholding of social signs [7]. Interestingly, even the strangest robots with an animated face for a monitor and speech synthesizing speakers can elicit social acceptance of their intention to fit in [29]. However human action may not square with perception, as children can interpret robots as humanoid and deserving of acceptance, but still physically abused them out of curiosity [15].

2.3 Machines interpreting human behaviors

If humans are so susceptible to machine influence, are machines also influenced by us? If we know what machines are seeing, we may be better able to critically evaluate what we see in them. Face recognition and detection has been used ubiquitously in cameras, cell phones, and computers. The data accumulated, however, provides a profile of the user, and may be exchanged or repurposed for influencing human behavior [30].

Seeing from the point of view of machine as a computational human may inform us of how algorithms can be biased [18], or how to avoid their gaze. Another approach is creating machines that physically interact with humans and see, through repeated physical interactions, the biases exhibited by machines and humans [24].

2.4 Multi-agent contexts

While the majority of studies has looked at single machines or devices, it is increasingly important for humans to have an understanding of what we see in networks of devices. Do we see a family when we see a machine nurturing (tapping over) another one of the same type? Do we see a loving couple when two machines are circulating around each other? Do we see conflict when networks of IOT devices seem to be at cross-purposes? Understanding how our human view of machines in network communities with each other differ from what they are actually doing in practice provides a way to identify our own perceptual biases.

Work with a group of robots shows that robot ensembles are capable of making people conform to their collective answers in a game where they choose a card that best represents a particular word [23]. This version of the Asch experiment shows that robots have collective presence just as humans. Robot groups can also collaboratively accomplish tasks like disassembling to move past a fence or swarming together in different patterns on a terrain [16]. However more research is needed to understand human perception of these swarms.

In terms of art and design, *My Keepon* is a robotic plush toy that pans, tilts, and rolls, evoking human-like characteristics that can notate group behaviour [2]. An approach with movements more coordinated amongst the robots would tell a more coherent story. *Penguins Mirror* is a work of 450 robotic penguins that rotate so as make out the shape of the viewer's body en masse [22], and similarly, *Audience* is a room of tiny mirrors that each look up and follow a human when she visits, reflecting herself [10]. These work, however, are interactive only in the way they gaze at us. To study how devices with agency and personality interact with humans, we create machines that exhibit different behavioural patterns when they are being looked at vs. ignored.

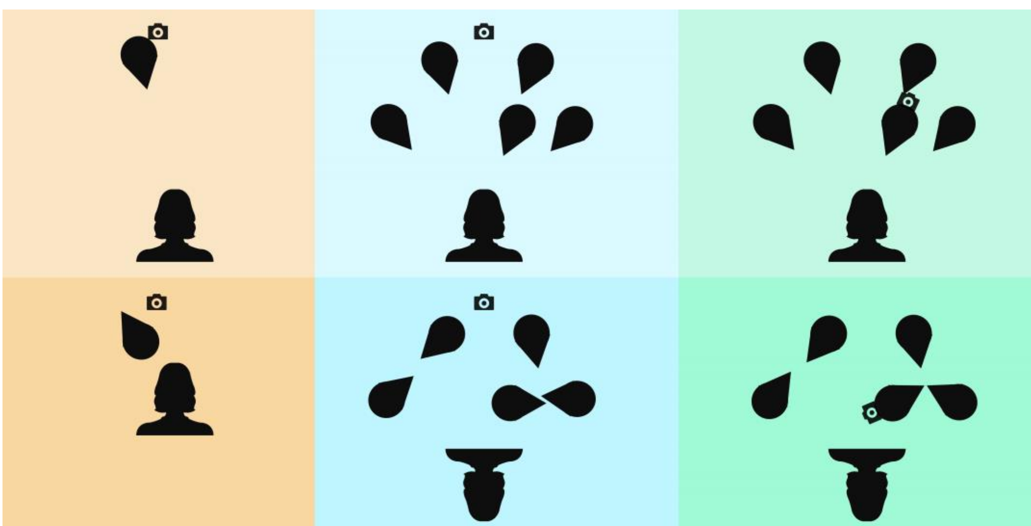

Figure 2: (Left) Single robot interaction (lamp). (Middle) Group interaction with fixed camera. (Right) Group interaction with camera mounted on the leader. Top row: when human face is detected. Bottom row: when face is close by or not detected.

3 METHODS AND OUTCOMES

3.1 Single robotic agent

I posed a hypothetical question that since we stare at our machines all the time: computers, cell phones, TVs, etc., how would we feel if they stared back at us? To study how humans interpret simple gestures of machines being watched, I built a lamp which tracks the human face from afar, but which turns away when humans get near (Figure 2 Left). The base of the lamp rests on a lazy susan which rotates in place with a servo motor attached to it and the base of the platform for panning. Another servo motor provides the tilt by moving the head of the lamp towards the ground or the sky. The light bulb is mounted on the bulb holder attached at the stalk of the lamp, and connected to a light dimmer module. An Arduino Uno board attaches to the dimmer as well as the servo motors, and an ultrasonic distance sensor (Figure 3). The servos are powered by external AA batteries, while the Arduino connects to the computer via USB. The computer is also connected an external webcam, which is placed next to the lamp. The Processing code on the computer runs OpenCV to detect faces in the scene. When the face is found off center of the camera, Processing sends a command via serial communication with the Arduino to move the panning and tilting motors incrementally to return the face to the center of the view. Meanwhile the ultrasonic sensor captures the distance from the human to the lamp, and interrupts the process to move the motors so that the lamp turns away if the human is closer than approximately 1.6ft. In a later iteration, I also used the size of the face detected in OpenCV to determine when to turn away.

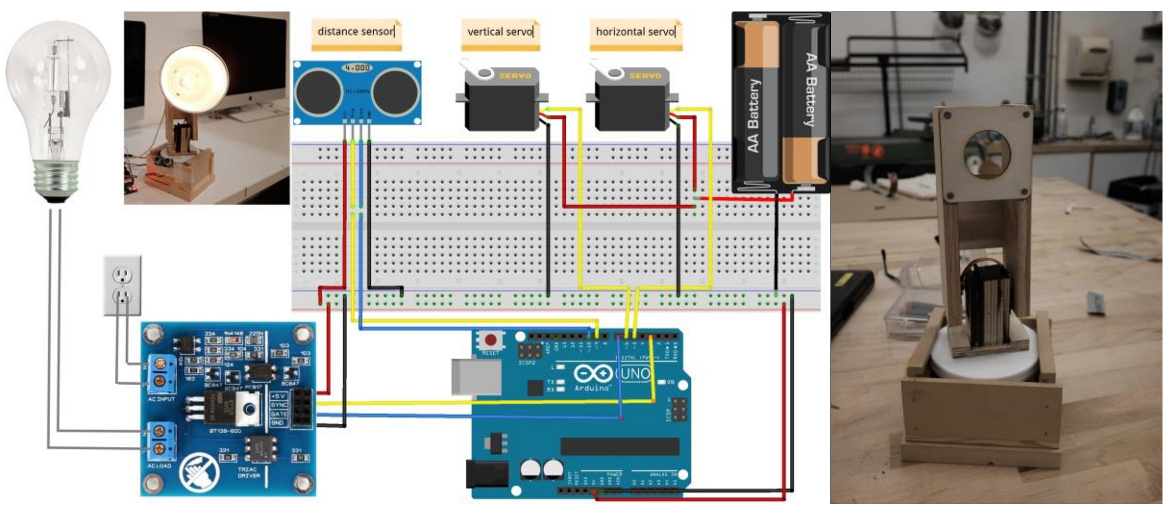

Figure 3: (Left) Connection diagram of lamp system (Not shown is the computer, which is connected to the Arduino and to an external webcam placed next to the lamp). (Right) Skeleton of the lamp body: a servo motor sits under the lazy susan.

Next I deployed the robot and let audiences play with it without instruction. I recorded (1) how people interacted with it in terms of using gestures, (2) what people's subjective experiences with the lamp in interview and in survey form (Likert scale 1 to 7) in terms of expressiveness and responsiveness. The former measures how useful the lamp's gestures are in conveying the personality trait of "shyness," while the latter measures how well the physical mechanisms of the machine is able to implement the trait (Figure 4).

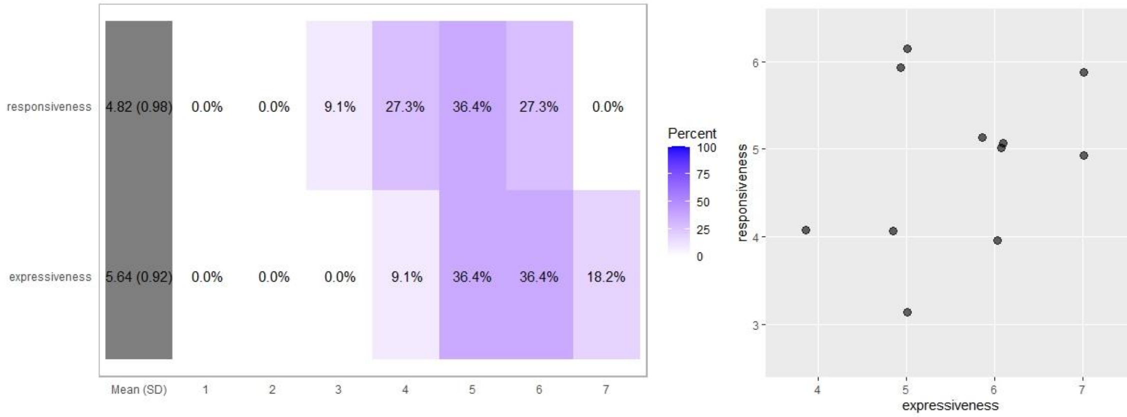

Figure 4: (Left) Heat map of responses to 1-7 Likert scale question of “how responsive was the robot?” and “how expressive was the robot?” with 1 “not at all” and 7 “extremely” (n=11). No significant difference between results from the two questions (Wilcoxon rank test p>0.05). (Right) Scatterplot with jittered response result (for visualization). Polychoric correlation R=0.4.

In addition to the surveys showing the lamp may be perceived a bit more expressive than responsive, I also found that audiences invented some unexpected ways of interacting with the lamp. One girl crawled under the table on the left side and emerged on the right side, where the lamp quickly moved to follow her face (see Video). This gives the impression that the lamp is all-knowing from afar. But at middle distances, participants overwhelmingly described the lamp as curious, as it continues to track their faces. Another unexpected gesture that gave the impression of curiosity is switching between audiences when multiple participants are in the room. The lamp has no preference for one face or another and hence would move from staring at one face to staring at another. A personality trait hence emerged from the omission of control for a particular situation (Figure 5).

Figure 5: (Left) A participant interacting with the lamp. (Right) Lamp in crouched position indicating shyness.

In another episode, a participant figured out that to make the lamp shy away, he doesn’t have to move his body, but rather reach out with his hands to interrupt the path of the ultrasonic sensor. This makes the lamp rather slavish as opposed to shy. To correct for this, I began using the OpenCV face rectangle size to determine when to shy away as opposed to using the ultrasonic sensor. Perhaps the most consensus insight is how much fun participants had with the lamp, as its combination of curiosity and shyness led to one participant calling it "cute" and wanting to take it home.

3.2 Robot groups in narrative

It's easy to guess the interactions with one machine, but what if a set of machines stared back at us? There's an immediate sense of being watched and conformity evoked just by increasing the numbers. What does a network of unified or contrasting machines evoke in us? Will we see their individual personalities, agencies, and their own individual stories? I made a flock of pan-and-tilt machines based on the design of the lamp that are connected to a single camera for tracking human faces. Instead of distance, the key variable of the interaction I thought was whether a face is detected. The metaphor was that when humans are not looking, the machines have their own secret lives to live, and their own stories to tell. But when human faces are found, all the machines in the flock look at them in solidarity in an attempt to evoke a sense of curiosity (Figure 6).

Figure 6: (Left) A participant interacting with the flock before being detected. (Right) The flock converges on detected face.

Two groups of agents following different rules of behaviour initially. One set (Figure 2 Middle) follow human faces using a stationary camera on the back of the platform that keeps track of view locations. When the user moves out of view, the group of agents start chatting and dancing, but when faces come into view, their locations are updated and the agents all look directly at them in alignment. Another set of agents (Figure 2 Right) follow a single camera mounted on one agent which tracks only the human face that it can see. Here, the viewer has to actively engage the camera before the group of agents can follow her. The machine doesn't have to build a model for where the user is; it moves towards the viewer if a face is found in the field of view of the leader.

This distinction between the two groups of machines is the model-based vs. model-free AI algorithms found in artificial intelligence research [25] (Figure 7). The former constructs a model predicting where human faces are found and responds decisively when one is found, but it cannot generalize well in new situations where the terrains are different for the calculations. The latter keeps track only of a way of moving towards faces, a heuristic that moves itself to the right when a face is detected in the left side of the pixels, etc. It can't detect all faces in the environment, but it can generalize to any situation where faces exist, even outside the platform.

When audiences interacted with the system, they noticed that the model-based system can track their face fairly reliably, albeit after a slight delay. They often call it "cute but creepy," but when I turned a few of the agents of the model-based system into ones that do their own tasks without tracking faces, viewers find it much more natural and non-threatening, much like a “cute flock of owls.” Although users had the most trouble with the model-free system (the agent with the camera attached and its associated followers), surprisingly they found it the most temperamental and “human-like.” Perhaps it is because that system forces the user to move their face into the agent’s field of view in order to be tracked, so the users are forced to “get the robot’s attention,” much as “prima-donna” type personalities in the real world. This mixture of a “self-centred” model-free system and a “reliable” model-based system give the users the richest experience where the members of the flock appear to show emotionality to those interacting with them. Viewers also invented playful games on their own, including two players showing their faces one at a time while giving hi-fives; and another playing “hide-and-seek” with hands over their faces as long as possible while facing the camera and escaping detection (see Video).

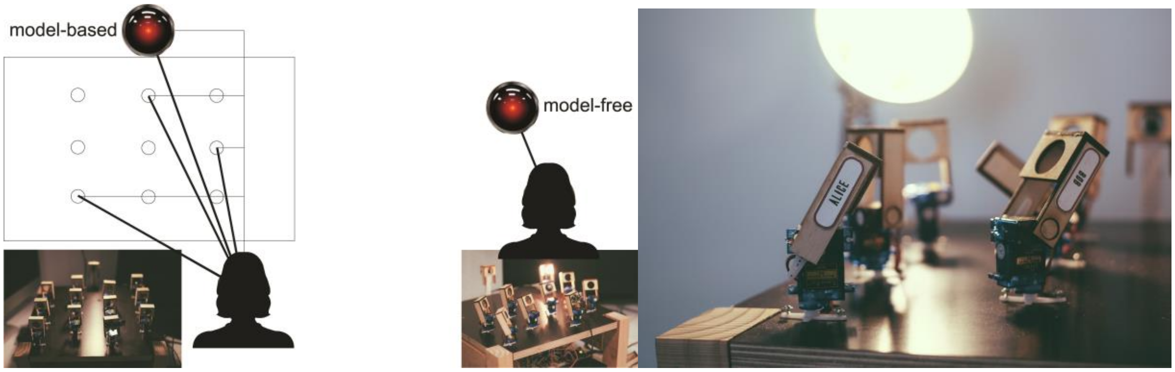

Figure 7: (Left) Model-based vs. model-free calculations of where the viewer is. (Right) Alice and Bob meeting and making a back-and-forth motion in a *Romeo and Juliet* story only when no audience faces are detected (or faces are hidden).

For human interaction, I programmed the systems to perform a script when no faces are detected. For example, I produced a “Romeo and Juliet” script in which “Alice” and “Bob” agents shyly stand next to each other “in public” when their compatriots are tracking viewer faces. When viewer faces are not found, the other agents do their own activities, and “Alice” and “Bob” are able to “meet” (i.e. turn towards each other) and consummate their love. It took a few attempts for viewers to understand this, but once they did, they found the story amusing, and began assigning emotionality to behaviours of the flock that depend on their interactions with us. Eventually they gave labels to these characters in the play and I put stickers on their frames like “Hope,” “Vanity” (for the leader), “Slacker,” and “Paparazzi.” The act of seeing has engaged a new dynamic in the network where characters alter their connections with each other based on audience interaction.

4 SUMMARY

Using single and groups of machines, I showed how personalities and stories emerge from playful “looking” interactions with machine gestures. Artistic interventions allowed us to examine machine behaviours amongst themselves as well as behaviours synchronized in some way to us. We begin to see personalities like curiosity and shyness; and relationships like flocking behaviour reminiscent of birds, internal conflict of fractions within the group, the rebellious maverick of the group, even love, care, or desire? Given the limitations of testing for the machine flock, more work is needed to measure human biometric response to machine interactions. The embodied interactions would benefit from life-sized interaction paradigms that reveal the use of human gestures.

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