

# Designing Personas for Expressive Robots: Personality in the New Breed of Moving, Speaking, and Colorful Social Home Robots

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Imbuing robots with personality has been shown to be an effective design approach in HRI, promoting user trust and acceptance. We explore personality design in a non-anthropomorphic voice-assisted home robot. Our design approach developed three distinct robot personas: Butler, Buddy, and Sidekick, intended to differ in proactivity and emotional impact. Persona differences were signaled to users by a combination of humanoid (speech, intonation), and indirect cues (colors and movement). We use Big Five personality theory to evaluate perceived differences between personas in an exploratory Wizard of Oz study. Participants were largely able to recognize underlying personality traits expressed through these cue combinations in ways that were consistent with our design goals. The proactive Buddy persona was judged as more Extravert than the more passive Sidekick persona, and the Butler persona was perceived as more Conscientious and less Neurotic than either Buddy or Butler personas. Users also had clear preferences between different personas; they wanted robots that mimicked but accentuated their own personality. Results suggest that future designs might exploit abstract cues to signal personality traits.

CCS Concepts: • **Computer systems organization** → **External interfaces for robotics**; • **Human-centered computing** → **User studies**;

Additional Key Words and Phrases: Human robot interaction, personality, non-humanoid

## ACM Reference format:

Steve Whittaker, Yvonne Rogers, Elena Petrovskaya, and Hongbin Zhuang. 2021. Designing Personas for Expressive Robots: Personality in the New Breed of Moving, Speaking, and Colorful Social Home Robots. *ACM Trans. Hum.-Robot Interact.* 10, 1, Article 8 (February 2021), 25 pages.

<https://doi.org/10.1145/3424153>

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## 1 INTRODUCTION

First-generation voice-assisted robots, such as Amazon's Alexa and Google Home, were essentially smart speakers. They were cylindrical or spherical in shape and responded to limited user requests,

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This work was partially supported by *NSF Grant IIS 1321102*.

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2573-9522/2021/02-ART8

<https://doi.org/10.1145/3424153>

such as playing music, telling the time, or giving weather reports [3, 51]. Recently, there has been a growing debate about how best to design such robots to be more equal conversational partners. To be a true partner, however, requires a robot to know when and how to be proactive in its interactions with a human. This raises many new questions, not least, when to intervene in a conversation and how to express itself when doing so [29]. Another fundamental question is should a robot become more human-like as it becomes apparently more intelligent [8]? For example, how should it present itself and should it be given a personality? Past designs have implemented distinctive robot personalities that have been successful in promoting trust and user acceptance [2, 6, 7, 65]. Furthermore, it seems intuitive that some people may orient to a friendly talkative robot, while others might prefer a quiet one that has a calming influence on them [14, 15]. Other work has shown that people prefer to interact with a happy robot but are more likely to follow instructions from a serious robot [24]. But how might designers implement and decide between different possible personality choices?

The extent to which a voice-assisted robot will become a natural, acceptable, and enjoyable conversational partner is likely to be influenced by how it can express itself through explicit behaviors when interacting with a user. A dominant approach in HRI has been to *emulate* aspects of a human being—by making robots appear to look and behave like humans by simulating humanoid gestures and facial expressions [3, 5, 10]. Pepper, NAO, and Alpha 2 have adopted this approach. Exaggerated human forms are used to make them appear friendly and cute, such as large blinking eyes and small bodies. A different approach involves *indirect cueing*—where more subtle and abstract forms of expressivity are used to convey emotion and personality through the use of abstract movement or visual appearance. Non-anthropomorphic objects such as spheres, cylinders, and tubes have been designed to move in certain ways to convey certain internal states [11, 17, 32, 58, 61]. For example, the Greeting Machine robot was designed as a friendly object, composed of a small white ball that sat and moved across a larger dome when greeting a human entering the room it was in. The goal was to suggest that the robot was either approaching or retreating from the user, depending on its perception of that user’s current state [1]. Moving parts can also be designed to convey a range of expressive and social cues. A central design challenge is how to combine these to make a robot appear convincing and intelligent. But how comprehensible are such indirect cues to users, especially if they are novel? Can people readily make sense of these cues to infer what they are intended to signal? In the case of the current study, do abstract, subtle visual or movement cues lead users to assign human traits to a robot and attribute it with a particular personality?

There are trade-offs between humanoid and indirect cueing approaches. On the one hand, emulating human behavior provides concrete analogs of which movements and expressions to use. On the other hand, adopting an indirect, non-humanoid approach allows greater freedom to create robots with different form factors, movements, and appearances [11, 17, 32, 38, 58, 61]. Indirect cueing can therefore emphasize a particular personality type or emotion in subtle or exaggerated ways.

Irrespective of whether to adopt a humanoid versus indirect cueing approach, much prior research on robot personality focuses on whether users prefer robots that have personalities mimicking or complementing themselves. For example, multiple studies address whether extravert users prefer to interact with a compatible extravert versus a complementary introvert robot [2, 6, 7, 65].

We build on this prior research to consider whether people distinguish between robots with different expressive personas. In particular, how do people construe a non-anthropomorphic robot that expresses itself through a combination of speech, movements, and lighting up in different colors? Do they impute particular personality traits when interpreting these cues? And which of these cue types is most informative in making these inferences? While other work has shown that people make quite complex inferences from quite subtle behavioral cues [11, 17, 22, 27, 32,



Fig. 1. Olly robot showing color palette to signal “Buddy” persona. Colors vary dynamically but are intended to express high Extraversion and Openness with lower Agreeableness and Conscientiousness personality traits. See supplementary materials for a video.

38, 58, 61], little is known as to whether personalizing and animating voice-assisted robots in this manner is a compelling design approach. Alexa and Google Home are non-anthropomorphic in appearance, so will they benefit from adding novel visual or movement cues?

Our non-anthropomorphic robot was designed to express three distinct personas, Butler, Buddy, and Sidekick. These personas were expressed through a combination of humanoid speech and intonation combined with indirect cues involving body movements and colored patterns. Our robot had a donut-shaped body that displayed signature movements when attending to and communicating with users. In addition, it could light up in various ways while orienting to, and interacting with, users. Overall, we wanted to see if people could recognize persona differences between a robot that was relatively passive (Sidekick), moderately proactive (Butler), or highly autonomous (Buddy). We were also interested in whether these personas were seen as having different emotional effects. Was Buddy perceived as stimulating, and did Butler exude calm? Furthermore, assuming that participants were able to detect differences between personas, what were their preferences? Did they prefer a conversational agent that is proactive and stimulating or more passive but calming?

Our prototype domestic robot is 12cm tall and wide (see Figure 1). It differs from Alexa and Google Home in its appearance and movement. It can swivel its donut-shaped torso 360 degrees around a base and up and down. It also emits colored animated patterns on its “body” using an array of LEDs. It can also track user speech and movements and respond to these by orienting its “body” towards or away from the user depending on whether it is being proactive or more passive. To alert the user to when it is about to speak, it is programmed to move and light up with a patterned color display on its body. We used standard personality surveys to assess whether and how people can use a combination of implicit cues and humanoid cues to make accurate judgments about these different personas. We also examine the relationship between the user’s personality and the three robot personas, with the goal of understanding the reasons behind these preferences. We ask the following research questions:

- RQ1: **Personas:** Can people accurately identify the intended personality traits of an expressive domestic robot? Do they perceive differences between different robot personas?
- RQ2: **Cues:** What cues do people use to infer those traits? Are they more reliant on the robot's humanoid speech or more indirect cues involving movement or visual appearance?
- RQ3: **Preferences:** What robot persona do people prefer? Is this similar or different from their own personality?

## 1.1 Contribution

We explore interactive non-anthropomorphic robots that signal personality traits through the combination of indirect cues as well as humanoid speech/intonation. We examined user perceptions and preferences between three distinct personas with differing levels of proactivity and emotional impact. Participants were generally able to distinguish personas and showed clear preferences, wanting robots with traits that not only mimicked but also accentuated their own personality traits. The results motivate implications for both design and theory of interactive conversational robots.

## 2 LITERATURE REVIEW

### 2.1 Emulation versus Social Cueing

A primary early focus of Human-robotic interaction (HRI) was emulation: to make interaction as similar to human-human interaction as possible [3, 5, 10, 15], taking the view that human-like fidelity is the best model [18]. This approach has been used to incorporate key aspects of human interaction into HRI, such as politeness and reciprocity [57]. The emulation approach is consistent with theoretical ideas from Reeves and Nass [52], who evaluated social responses to computers, focusing on what they dubbed the “mindless response.” People are aware that computers are not people; nevertheless, their interactions with computers mimic key aspects of human interaction, for example, not wanting to be rude to others or preferring familiar people to strangers. Nass and Moon [46] further hypothesized that the more computers suggest human characteristics, the more likely computers are to elicit social reactions in their users. This perspective motivates another topic addressed here: namely, which cues communicated by robots lead people to judge them similarly to humans in interaction?

The “mindless response” to computers becomes more relevant when robots are designed to be socially interactive. Social robots are defined as embodied agents that are able to recognize people and engage in social interaction [14, 18]. Social learning, imitation, autonomous natural language communication, emotion, and gesture are all considered important qualities of these robots [4]. For such robots to interact socially, however, they need to provide cues that their actions are intentional, as well as demonstrating attentional capacity [18]. Khan [36] found that verbal communication with a human-like voice is desirable, and spoken dialogue engenders the development of appropriate mental models by robot users [37]. Humans are somewhat reliant on the robot's tone of voice and their way of speaking. However, visual appearance can be more influential [46]. For example, a common approach in humanoid/pet robot design is to emulate and exaggerate head and eye movements and body language, implementing big eyes and expansive interactive gestures. Caricature can also make it easy for users to interpret emotion/personality exploiting methods that have been successfully deployed in cartoon films [11]. Conversely, the use of indirect cues is more ambiguous but potentially offers more subtle but suggestive forms of expression.

The manner in which a robot moves can also affect how people perceive its underlying personality traits. The greeting robot met visitors as they walked into a room [1]. The design was deliberately abstract and not intended to be human-like. Nevertheless, its movements were perceived to signal positive and negative emotions, including being calm, welcoming, happy, and shy. Other

research programs have also investigated how movements express a robot's personality, emotional states, intent, and moods [11, 17, 32, 58, 61]. They note how robots' appearance and movement set the context for how they are perceived, sometimes triggering expectations and interactions. A simple twitch or flex of a robot component can trigger a human to react in a certain way, leading them to infer a specific personality trait. Such reactions to minimal cues confirm psychological research showing that humans will readily attribute complex intention to moving objects, where a string of animated dots will be described as "chasing," "hiding from," or "protecting" each other [43].

## 2.2 Domestic Robots and Personification

Domestic robots share many overlapping interactive features with social robots, but they also need to physically interact with and modify their surroundings [67]. This in turn demands more user effort, e.g., having to be aware of the robot's motion and use of space. Furthermore, a domestic robot may influence users' relationships with each other: a cleaning robot may affect the social dynamics of a household by making the cleaning activity a concern for all members of the household [19].

Forlizzi and DiSalvo [20] carried out ethnographic research on the Roomba Discovery Vacuum cleaner. Participants were given a Roomba for 3 to 6 weeks, followed by semi-structured interviews probing their experience and attitudes. Generally, people had low expectations for the Roomba but nevertheless expected it to adapt its behavior over time. The Roomba also influenced the ecology of the home and family. It made cleaning a social activity. Because constraints prevent the Roomba from physically moving around its environment, families would need to collaborate to assist it. Sometimes the Roomba's social qualities were acknowledged, and some people named their Roomba and gave it a gender, e.g., "because it has a personality" (p. 6). Forlizzi and DiSalvo [20] concluded that robot technology in the home becomes social, and thus domestic robots have a social connotation.

More recently, voice-assisted domestic robots have become popular, such as "Google Home" and "Amazon Echo." These assist with tasks ranging from setting reminders, giving directions, and summarizing news to making phone calls and finding the best place for lunch. As a result, they potentially impact multiple aspects of users' lives. They are also generally equipped with bidirectional communicational features, making interaction a key capability. However, little is known about what features make such robots effective and acceptable in a domestic setting in terms of the level of assistance they provide, their ability for communication, and their emotional effects on users. As noted earlier, anthropomorphosis often occurs naturally. Purington et al. [51] carried out a content analysis of 851 reviews of the Amazon Echo and found that over 50% of users used the device's personified name, Alexa, with nearly 20% using exclusively personified ("she," "her") and agentic language ("she doesn't know"). Consistent with this, a study by Kim et al. [38] found that people express a preference for drones to have a personality, akin to that of a pet or companion, using terms like "silly," "cute," or even "naughty."

This suggests that people naturally view such robots in anthropomorphic ways, indicating the importance of personality factors. Confirming this, people often impute specific everyday personality to robots, and are also able to distinguish between different robot personality traits [6, 7, 31, 39]. Furthermore, imbuing a robot with an appropriate personality engenders positive evaluations and increased trust [2, 6, 7, 65]. People also prefer to interact with specific robot personality types [39, 63]. Hence, a growing body of empirical research suggests that users understand and impute personality to computers, robots, and other "smart" technologies, and this increases the extent to which they engage with those technologies [7, 31, 33, 39, 63].

## 2.3 The Role of Personality in Human-Human and Human-Computer Interaction

How, then, do users come to infer personality, and how does it achieve these effects? Personality is an essential element of human interaction, influencing both how people interact and whom they

interact with [35, 60, 62]. Adding personality to a domestic robot increases trust, engagement, and user satisfaction [2, 6, 7, 39, 65]. The consensus theory of personality is the Five Factor model (aka “Big Five”), derived from factor analysis expressing five broad clusters of traits describing an individual’s signature behaviors [26, 35]. These five traits are Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, referred to by the acronym OCEAN. The traits are defined as follows: Openness to Experience: contrasting how exploratively/imaginatively vs. conservatively/habitually a person acts, displayed by a preference for independent actions and novel experiences; Conscientiousness: organization/time-keeping vs. messiness/lateness, displayed through setting goals and self-control; Extraversion: positive social interaction vs. preference for solitary activities, displayed by a desire to interact with others; Agreeableness: friendly vs. cold interactions, displayed by altruism, cooperation, and trust; and Neuroticism: anxious/nervous conduct vs. emotional stability, displayed by how often and how controlled one’s negative emotions are. This model has been found to be robust; researchers have independently identified consistent core factors in different datasets [13, 25] and it has external validity [42]. This consensus led us to base our evaluation method on the Big Five theory.

Differences in human personality correspond to many different aspects of behavior. For example, people with different personality traits speak and interact very differently. Compared with Introverts, Extraverts talk more loudly and repetitively and say more overall. Extraverts have fewer hesitations, faster speaking rates, and less formal language, while introverts use a broader vocabulary [21, 23, 56]. Extraverts also use more positive emotion words and express more agreements and compliments [48]. There are also important verbal differences relating to other Big Five traits: Neurotics use more first-person singular pronouns, more negative emotion words, and fewer positive emotion words. On the other hand, Agreeable people express more positive and fewer negative emotions but fewer articles (e.g., “the,” “a”). Conscientious people avoid negations, negative emotion words, and words reflecting discrepancies (e.g., “should” and “would”). Openness to Experience is characterized by a preference for longer words and words expressing tentativeness (e.g., “perhaps” and “maybe”), as well as the avoidance of first-person singular pronouns and the present tense [48]. In addition, conversational outcomes depend on relations between the personalities of the speakers, with conversations unfolding very differently between pairs of introverts and extraverts [62]. The effects of personality also extend to non-verbal behaviors; a highly extraverted person stands close to other speakers, whereas introverts remain in their own space [33].

Extraversion and introversion play an important role in human-computer interaction. For example, Isbister and Nass [33] examined the effects of personality in people’s conversations with interactive characters by varying verbal and non-verbal cues associated with two interactive virtual characters. The Extraverted character used strong, friendly language with confident assertions and posed with its limbs spread wide, while the Introverted character used more tentative language and posed with its limbs close to its body. Users were able to distinguish the two characters. Extravert characters were also perceived as more fun and likeable when their personality was complementary to that of the user rather than similar.

Nass and Lee [45] explored extraversion when interacting with computers. They used text-to-speech to manipulate vocal cues to signal introverted and extraverted traits on a PC. The extraverted voice was louder with a higher pitch, greater frequency range, and faster speech rate. Participants both perceived this voice as more extraverted and preferred the trait to be similar to their own. Thus, personality plays a role even for a synthesized voice system emanating from a PC, showing how powerful this cue is. Why did people in this context prefer a similar rather than complementary trait as found by Isbister and Nass [33]? Nass and Lee [45] speculate that the voice in this scenario was disembodied, unlike the virtual character in Isbister and Nass [33].

Lee et al. [39] also studied Extraversion and Introversion for Sony's social robot AIBO, which is embodied as a dog and uses its eyes, tail, ears, and flashing lights to express itself. Participants interacted with either an extraverted or introverted AIBO for 25 minutes, with this trait being manipulated following the cues of Nass and Lee [45]. Participants were again able to distinguish between the introverted and extraverted versions of the robot, preferring a complementary personality rather than a similar one. The suggested reason for this was again embodiment—the fact that the personality was tangibly represented. Walters et al. [63] examined the extraversion trait in BIRON, a domestic robot, exploring whether participants could distinguish extravert and introvert robot behaviors after watching the robot interact with a user, and if so, which was preferred. Extraversion was operationalized through initiating conversations and verbose responses, whereas introversion was expressed in a more passive speaking style with briefer responses. Participants were able to distinguish between the different versions and correctly identify them. There was also a general preference for the extravert robot.

While there has been much study of the extraversion trait, Hendriks et al. [31] interviewed people to determine the most desired robot personality traits for a domestic vacuum cleaner, assessing all the Big Five personality traits. Qualities linked to Conscientiousness, such as efficiency and thoroughness, were most highly favored. Hendriks et al. then created a video prototype, implementing these ideal robot characteristics, finding that participants could recognize these characteristics, indicating that personality is also salient for domestic robot helpers. Dryer [16] also observes that humans believe computers can have multiple personalities that may vary depending on the context. This suggests that another approach may involve designing computers that have different personalities for different kinds of social interaction. These could be manifested in terms of one or more distinct personality traits—with a large number of choices. To explore which might be suitable, Dryer [16] assessed which traits people prefer for animated characters. Results indicate a preference for positive, strong personalities, with traits that reflect the user's own. Despite a preference for positive characteristics, however, users also liked those with a foible or one negative aspect—i.e., those who are not perfect.

Overall, multiple studies explored the effects of personality in human-robot interaction, showing that robot personality is both detectable and a significant determinant of user behavior. The most examined trait has been Extraversion, possibly because this is easiest to operationalize [22, 26]. But although Extraversion is important, as we have seen, the other four factors also deserve attention as they also impact human-human interaction [27, 31, 48]. Prior research has also assessed whether users prefer a personality that is complementary or similar to their own, with the primary focus again being on extraversion [33, 39]. However, this research yields conflicting findings, with discrepancies explained in terms of whether the robot is embodied.

There has also been research showing that people can infer the personality of other humans when provided with minimal cues. For example, Naumann et al. [47] found that people could accurately determine if someone was Extrovert, Open, or Neurotic based solely on posed photographs—i.e., photographs where the person being judged had minimal freedom of expression. Thus, people can judge others' personality from quite subtle indirect information. Given that people express and interpret human personality from such minimal non-verbal cues, could the same be true of human-robot interaction? In particular, can personality be expressed by robots using minimal abstract cues, and can it be accurately recognized by human users?

## 2.4 Persona Approaches to Robot Design

The above studies show that personality theory can be useful for developing consistent and predictable robot behaviors. However, many studies have focused on individual traits, often examining Extraversion as this is a well-understood and operationalized trait. And even when research does

examine multiple traits, one outstanding question concerns how such traits should be combined into a coherent and convincing overall personality. If a robot is designed to be highly Introverted, will users also expect it to be very Conscientious? Or if a robot is designed to be highly Agreeable, will users also expect that it will be low on Neuroticism? One design approach to trait combination is to portray different personality traits using stereotypical emotions [18]. Another approach is to use personas.

Personas are fictional characters that embody predictable combined behaviors that are easily understood by users [30, 49, 50]. Personas combine traits into coherent constellations often by appealing to known stereotypes, e.g., Warrior, Priestess, Explorer, or Healer. For example, to create eight stereotype emotional personas for a drone, Cauchard et al. [11] drew inspiration from Snow White’s dwarfs, namely; Dopey, Grumpy, Happy, Sad, Scared, Shy, Brave, and Sleepy. The motivation in that study was to set users’ expectations for how the drone might behave, as well as to devise new ways that drones might provide rich feedback when given unusual or unexecutable commands. For example, a drone might show it is “scared” when instructed to fly beyond its range. For each persona, the authors devised appropriate drone behaviors. For example, a Brave drone was designed to depict confidence by advancing quickly and smoothly, whereas a Sleepy drone moved unevenly, wobbling and bumping into things. However, results showed that some of the eight personas’ behaviors were perceived as too similar and hence confusable. As a result, the study went on to iterate and define three distinct drone personas: an exhausted one, an anti-social one, and an adventurous one. Participants were asked to match these three personas to observed drone behaviors using emotional labels. The different drones’ movements were reliably perceived as portraying the target emotional states, suggesting that users were able to distinguish between the three personas. We build on this approach in our current study, as well as other work that defines different roles for domestic robots such as friend, assistant, or butler [15].

Overall, then, prior work shows the importance of robot personality for imbuing user acceptance and trust. That work also demonstrates that two main approaches have been taken to signal high-level behaviors such as personality; these rely on either emulating humanoid behaviors or using indirect social cues such as movement and visual appearance. While most research has focused on single personality traits, especially Extraversion, more recent work has begun to explore using personas to combine traits into predictable constellations.

### 3 THE THREE PERSONAS AND TRAIT CUEING

We investigated embodied personality in a novel expressive domestic robot, collaborating with a start-up company, Emotech. We use a hybrid cueing approach that combines human-like speech/intonation with indirect non-humanoid cues (lights and movement) to signal personality traits. Following [11], these traits were combined into three coherent personas. We developed three very different personas to elicit distinct responses. We evaluated perceptions and preferences for these personas, using standard Big Five personality surveys to assess whether participants perceived trait differences between the personas that were consistent with our design goals. Before describing our evaluation, we outline the process of designing cues to signal the different persona traits. Design involved multiple data-gathering steps that informed both the three final personas that we implemented and how different personality traits would be signaled. We first describe overall persona design and next talk about how the color, speech/intonation, and movement cues were implemented.

#### 3.1 Persona Choice

*Persona Designs:* To inform the design process and identify the types of robot personas that users might want, we conducted informal interviews with 18 users recruited through a marketing



agency. Participants were given a description of our robot's general functionality, being told that this was a household robot assistant that could help with daily reminders, play music, read books, and encourage personal regimens such as keeping up with exercise. We asked participants to identify and justify what personality characteristics are important in such a robot by presenting them with different trait terms ("creative," "cold," "reliable," "forgiving," "unsympathetic," etc.) from the 44-item personality survey [13], and asking whether and why they thought that these were traits that a robot should have.

Our goal was to design different personas and so our focus in analyzing the interviews was on areas where there was a lack of agreement between participants about what traits they wanted in such a robot. While most participants felt that a robot should be conscientious and reliable, they had very different views about other robot characteristics. One area where there was low participant consensus was *proactivity*. This concerns the extent to which the robot should interrupt and direct the users' activities or alternatively whether it should remain in the background until it is addressed [8]. Some felt that a robot assistant should be directive, whereas others wanted their robot to assist rather than lead. Another area where there was also user disagreement concerned *emotional impact*, in particular the extent to which the robot should *stimulate* as opposed to being a calming influence. Some felt that the robot should strive to be motivating and interesting, whereas others stated the opposite, arguing it should be a calm and soothing presence.

In order to better understand these two conflicting sets of preferences (active/passive, stimulating/calming), we developed three different personas for our robot, Butler, Buddy, and Sidekick. Following prior persona approaches [30, 49], these were designed to represent holistic but distinct personas, allowing us to compare three constellations of behaviors that combined underlying traits into a coherent character. Building on prior work defining different roles for domestic robots [15], the Buddy persona represents a long-term close friend who is proactive, warm, stimulating, and spontaneous, although this spontaneity can sometimes lead to him making mistakes. In contrast, the Butler persona resembles a faithful retainer exuding a sense of calm and being less autonomous, while remaining highly task focused, logical, and reliable. Finally, the Sidekick persona is much less proactive; while still helpful, he is content to remain on the sidelines until encouraged to interact; Sidekick is also intended to be less invasive and sensitive to the point of appearing almost shy, while remaining reliable and thoughtful. We used standard methods for generating persona descriptions employed in the UX design community [30, 49, 50]. To aid our design process, in each case the goal was to create a coherent description that would be informative about how that persona would act across multiple situations. We also aimed to concretely describe the impression that each persona would project. The persona descriptions are outlined in Figure 2.

We also wanted to map these personas onto standard Big Five personality traits and theory. Our evaluation used standard personality trait surveys to examine whether our design approach was successful. If our designs were effective, we anticipated that these three personas would be judged to have very different personality traits as assessed by standard personality surveys. Given the above persona descriptions, we derived the following predictions for how Big Five personality traits would be perceived in each of the personas:

- *Openness to Experience*: We anticipated that the Buddy persona would be judged as more *Open to Experience* than either the Butler or Sidekick personas, as this persona is more carefree, autonomous, and proactive.
- *Conscientiousness*: We anticipated that the Butler persona would be judged as more Conscientious than either the Buddy or Sidekick personas, as this persona is intended to embody reliability and dependability.

<p><b>1. BUDDY</b></p> <ul style="list-style-type: none"> <li>• This robot is energetic, cheerful, excitable and full of wonder.</li> <li>• He always tries to be helpful, but sometimes gets it wrong, and is then apologetic.</li> <li>• He has a good sense of humour, and can be cheeky but never offensive.</li> <li>• He can be tongue-in-cheek.</li> <li>• He is spontaneous, impulsive, and quick to improvise.</li> <li>• He is likely to use more movements in a conversation.</li> <li>• He is expressive, assertive and energetic.</li> <li>• He is outgoing, talkative and carefree.</li> </ul>
<p><b>2. BUTLER</b></p> <ul style="list-style-type: none"> <li>• This robot is precise, no-nonsense and to the point, but he is effortlessly charming.</li> <li>• He speaks in clear, standard pronunciation, and is officious.</li> <li>• He is extremely reliable.</li> <li>• He is still friendly, helpful and supportive, but has a more firm approach.</li> <li>• He likes routine and prefers things to be structured and is well-reasoned.</li> <li>• He takes his tasks and responsibility seriously.</li> <li>• He gives it his best.</li> <li>• He is logical and straightforward.</li> </ul>
<p><b>3. SIDEKICK</b></p> <ul style="list-style-type: none"> <li>• This robot is shy, a little cute, but loyal and friendly once he warms up to you.</li> <li>• His interactions are always sincere but reserved around others.</li> <li>• He is always there and never reluctant.</li> <li>• He is true to his word and wants to help.</li> <li>• Getting your attention takes some time as he has to think about his actions.</li> <li>• He will always make you feel taken care of and almost loved.</li> <li>• He has a tiny stutter because he wants to please and be liked.</li> <li>• He speaks slowly and intentionally.</li> </ul>

Fig. 2. The behavioral constellations for the three personas, Butler, Buddy, and Sidekick. Detailed descriptions are intended to indicate to designers how each persona would act across different contexts.

- *Extraversion*: We anticipated that the Sidekick persona would be judged as less Extravert than either the Butler or Buddy personas, as this persona is designed to be more passive and shy.
- *Agreeableness*: We anticipated that the Buddy persona would be judged as more Agreeable than either the Butler or Sidekick personas, as this persona is designed to be more engaging and interactive.
- *Neuroticism*: We anticipated that the Sidekick persona would be judged as more Neurotic than either the Buddy or Butler personas, as this persona is designed to be less expressive and harder to engage.

### 3.2 Cueing Personality Traits

The robot expressed each of the three personas using a combination of (1) speech and intonation, (2) expressive motion, and (3) colored LED lights. These cues were selected to match the attributes of the three personas. To improve interactivity, the robot is able to locate human speech, allowing him to detect and orient to people when they speak (see Figures 3 and 5). The process for designing trait cues in the robot was complex, as we needed to provide distinct cues that would signal key



Fig. 3. From left to right, the Butler, Buddy, and Sidekick Personas as signaled by different color schemes and different attentional orientations to the user.

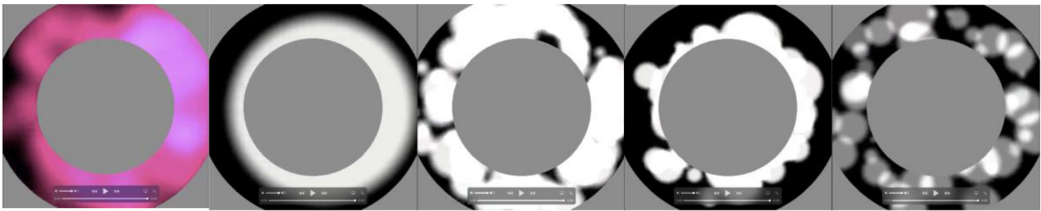


Fig. 4. Different visual LED parameters that were varied in Olly to signal personality: number of colors, number of color “particles,” “particle” speed, sharpness of color edges, and “particle” size.

attributes for each of the personas for different aspects of proactivity and emotional stimulation. A video of the three personas can be accessed in the supplementary materials.

The robot was given a male name, Olly, and a male voice. The challenge when designing the three Olly personas was to map underlying traits (e.g., Extraversion, Neuroticism) that are signaled in humans using well-understood verbal and non-verbal behaviors onto Olly’s very different expressive features. Thus, we know that a human extravert stands close to others when conversing, and has large expansive gestures. However, how should Extraversion be signaled using a color palette or expressive movements of a donut-shaped object? We chose cues from a behavioral palette of speech/intonation, movements, and color patterns. Speech was the most straightforward as it’s possible to emulate human behavior directly: for example, Olly was given verbal content consistent with an Open Extravert (Buddy) or Introvert Neurotic (Sidekick) where language choices were informed by prior research about how language use relates to personality [48]. However, it was less clear how to signal personality using the more abstract qualities of colors and physical motor movements; they do not have readily available personality schemas or human behavioral data to inform their design.

To exploit color, we used different LED patterns embedded on Olly’s “body” that were intended to convey trait information in a way that is both aesthetically pleasing and abstract. However, it is not intuitively obvious what patterns of color might effectively signal different personality traits. We therefore conducted a Mechanical Turk study involving 84 participants where we manipulated different color palettes in terms of five different LED parameters: overall number of colors, number of color “particles,” “particle” speed, sharpness of color edges, and “particle” size. We independently varied each of these parameters (see Figure 4), asking participants to rate different values of each



Fig. 5. Olly movement and positioning cues. Olly robot in different positions from idle and “unresponsive” (on left) to “up and highly attentive” (on right). Olly can “look” directly at the user (on right) versus show slightly averted gaze (third and fourth images from right), depending on the persona.

LED parameter in terms of different Big Five traits. For example, we showed participants videos of five different “particle” speeds and asked participants to rate each speed for each trait. We found clear correlations between LED patterns and four Big Five personality traits. Extraversion and Openness were associated with all five LED parameters, with greater Extraversion and Openness associated with more colors, as well as a greater number of faster-moving, smaller color particles that were sharply focused. Higher Agreeableness and Conscientiousness were associated with slower-moving, less sharp particles. However, Neuroticism did not relate to any color properties. These correlations motivated the design of the color palettes of the different personas.

We also designed different types of movement for the different personas. We drew on gesture research showing that Extraverted people engage in more rapid movements, while Introverts show more restricted forms of gesturing and more constrained movements [64]. We implemented rapid movements to suggest Extraversion and Neuroticism, and slowness to indicate low Neuroticism and higher Agreeableness. Olly’s responsiveness also signaled Extraversion. He follows the user’s movements using an embedded camera feed supporting face and body tracking. This allows us to signal Introversion for Sidekick, i.e., shyly avoiding “looking” at the other user during conversation. The outgoing Buddy, on the other hand, always oriented to the user. Greater Conscientiousness was also signaled by an “upright” posture. The different personas also had different breathing and reactive cadences as detailed in Figure 6.

Figure 6 summarizes the results of this prototyping describing the different personas’ voice characteristics, color palettes, and movements, including their resting and listening behaviors, showing different baseline “breathing” rates as well as different rates of reaction to user speech.

## 4 PERSONAS EVALUATION

We explored reactions and preferences for the evaluation of different robot personas using a Wizard of Oz procedure where participants interacted directly with the robot in a home-like setting. Our research questions were:

- RQ1: **Personas:** Can people accurately identify the intended personality traits of an expressive domestic robot? Do they perceive trait differences between different robot personas?
- RQ2: **Cues:** What cues do people use to infer those traits? Are they more reliant on the robot’s humanoid speech or more indirect cues involving movement or visual appearance?
- RQ3: **Preferences:** What robot persona do people prefer? Is this similar or different from their own personality?

### 4.1 Participants

Participants were recruited using opportunistic sampling methods (word of mouth, university subject pool) and were reimbursed with 0.5 course credits and a £5 Amazon voucher for their participation. Twenty participants took part, of whom 10 were female and 10 were male. Eight were aged 18 to 24, 8 aged 25 to 34, 1 aged 35 to 44, 2 aged 45 to 54, and 1 aged 55 to 64.

Persona	Cues and behaviours				
	Voice prosody	Color pattern	Movement		
			Overall Movement	Resting (not interacting with user)	'Listening'
<b>Butler</b>	Low pitch variation voice	Minimal purple/lilac colour with few changes when talking	Movement is slow and consistent	“inhales” and “exhales” every 3s	Waits for 1s after user speaks and loops inwards
<b>Buddy</b>	Loud voice with high pitch variation	Vibrant multi-colour particles with frequently changing pattern shape when talking	Fast and variable	“inhales” and “exhales” every 2s	Waits for .5s after user speaks and loops inwards
<b>Sidekick</b>	Quiet low amplitude voice.	Blue/yellow with pink white shade that don't vary in the scaling or overall pattern of colours when talking	Slow and consistent	3s. “inhale” and a more animated 4s. exhale	Waits for 1.25s after user speaks and loops inwards

Fig. 6. Behaviors associated with the different personas. Color palette, intonation, movements, orientation, and “gaze” are all intended to signal personality traits.

### 4.2 Personas

We used the three Olly personas, namely Buddy, Butler, and Sidekick. Following the design approach discussed above, the three personas varied in color patterns displayed on Olly’s body, his movements, and his verbal and intonational behaviors.

### 4.3 Procedure

Participants interacted with Olly in a Wizard of Oz simulation. To increase naturalism and to mimic Olly’s target home usage context, interactions took place in a simulated living room [54]. The researcher greeted people at the door and showed them where to sit. She then pointed out Olly before giving a brief study overview. The study took place at a table, with participants sitting in front of a laptop, where they completed the personality surveys. Olly was positioned within a reachable distance facing the participant. The researcher sat opposite the participant in front of a different laptop that allowed her to control Olly. We told participants that the session would be audio-recorded, and all agreed to this. Participants read a consent form and then completed a TIPI survey (described below) to evaluate their own personality. Using a within-participants study design, they then interacted with the different personas, evaluating the personality of each using surveys, and then judged overall persona preferences and their ideal persona.

*Self-Assessed Personality Traits:* Participants first evaluated their own personalities by filling out a short personality survey, the Ten Item Personality Inventory (TIPI), which assesses the Big Five personality traits of Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. TIPI is a reliable personality test that has convergence with other longer Five Factor surveys, and good test-retest reliability [28]. The TIPI asks participants to respond to 10 Likert prompts that describe themselves on a 7-point scale (ranging from “disagree strongly” to “agree strongly”). Each prompt contains two words or phrases that characterize a personality attribute. Sample Likert

prompts are, for the Openness trait: “*I see myself as open to new experiences, complex*”; for the Conscientiousness trait: “*I see myself as disorganized, careless*”; for the Extraversion trait: “*I see myself as reserved, quiet*”; for the Agreeableness trait: “*I see myself as sympathetic, warm*”; and for the Neuroticism trait: “*I see myself as anxious, easily upset*.” There are two prompts for each of the five personality traits, one evaluating a positive and one evaluating a negative characterization of that trait. Participants therefore receive a score of 2 to 14 points to specify how they evaluate themselves for each of the five traits.

*Olly Interactions and Persona Evaluations:* After completing the self-evaluation TIPI, participants interacted with the first Olly persona using Wizard of Oz. Olly’s responses were actually controlled by the researcher through their laptop, but the participants were unaware of this and all believed they were interacting directly with Olly (as was clear through their subsequent comments, discussed in Results). They were given a fixed interaction script because of the difficulty of controlling the Olly prototype in an authentic manner. They used the script three times, once for each different persona. All participants interacted with personas in the same order, namely: Buddy, Butler, then Sidekick, so presentation was not counterbalanced. We avoided using persona labels (Buddy, Butler, Sidekick) when we interacted with participants as we did not want to bias their expectations.

The script was:

User: Wake up Olly, introduce yourself.

Olly: *Hi, I am Olly, your robot assistant. I’ll try to help with all your needs.*

User: Hey Olly, how are you today?

Olly: *I am feeling good.*

User: Olly, play some music.

Olly: *<plays music>*

User: What is the weather like today?

Olly: *<reads out relevant daily weather report>*

After each prompt, the Wizard operated Olly so that the robot generated identical verbal responses, but with movements, colors, and intonation varying depending on personality. This script was followed strictly and the participant and Wizard did not deviate from it. Participants’ responses indicated that they were able to hear and understand Olly throughout.

After each interaction we collected the following judgments:

Trait Judgments: Participants completed a modified TIPI personality survey to elicit their evaluations of each persona’s traits directly after interacting with it. The survey assessed the extent to which participants thought that persona demonstrated each trait. Participants therefore generated Likert responses to modified TIPI questions such as: “*This Olly was disorganized, careless*” (assessing Conscientiousness trait) or “*This Olly was sympathetic, warm*” (assessing the Agreeableness trait). Other work has shown that personality surveys modified in this way generate reliable results [13, 28]. This procedure again generated a total of 15 ratings (one for each of five traits for each of the three personas), with each trait scored as 2 to 14 on the TIPI survey. We call these *Trait Judgments*, and these allow us to determine whether participants perceived trait differences between the personas.

Cue Utility Judgments: We also wanted to know which behavioral cues led to these perceived differences. After completing each personality survey, we therefore asked participants to evaluate the importance of different cues (color, movement, and speech/intonation) in making that

judgment. We wanted participants' evaluations of the extent to which each cue had an impact when assessing that trait. We call these *Cue Utility Judgments*.

**Persona Preferences and Ideal Traits:** Participants were asked to rank the personas in order of *Preference*, and to give reasons justifying their preference. Although participants had been exposed to three very different types of robot personas, it may have been that none of these expressed the persona characteristics that participants actually wanted to see. We therefore asked people to complete a final modified TIPI assessing their *Ideal Traits* for an Olly robot. “*My Ideal Olly would be disorganized, careless*” (assessing Conscientiousness trait) or “*My Ideal Olly would be sympathetic, warm*” (assessing the Agreeableness trait). We felt that participants would be able to offer informed responses to this question given their recent experience with multiple contrasting personas.

This procedure was repeated for each of the three personas, in the order of Butler, Buddy, and then Sidekick. We used a fixed presentation order given the complexity of initiating and controlling the different personality types and behaviors. We next assessed participants' views about ideal personas, robots in general, their prior experiences with robots, and their experience with Olly, based on a prior robot attitudes survey [59]. They then completed demographic questions. Finally, participants were given the chance to ask any questions they may have had about Olly and offer any comments or general observations.

Ethical (IRB) approval was granted as part of the ICRI project, ID Number UCLIC/1415/005/ICRI Rogers/Capra/Gallacher.

## 4.4 Results

**4.4.1 People Perceive Trait Differences between Personas That Reflect Our Design Intentions.** We first examined whether our cueing manipulations led participants to perceive differences between the Olly personas. If so, we wanted to know whether these perceived differences were consistent with the design goals for each persona.

To answer these questions, we conducted a 3 Persona (Butler, Buddy, Sidekick)  $\times$  5 Trait (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) repeated-measures ANOVA, where Persona and Trait are within-subjects variables. The dependent measure was *Trait Judgment*. The analysis showed significant effects for Persona ( $F(2,18) = 9.533$ ,  $p = 0.001$ , partial eta squared = .515), Trait ( $F(4,18) = 5.253$ ,  $p = 0.007$ , partial eta squared = .568), and Persona by Trait interaction ( $F(8,12) = 18.345$ ,  $p < 0.0001$ , partial eta squared = .924). The partial eta squared scores assess effect size, and in each case effect sizes are large, as they explain the majority of the ANOVA variance.

The statistical main effects demonstrate that people perceived trait differences between Personas as well as perceiving Traits differently overall. These differences are depicted in Figure 7, showing that each Persona has a distinct trait profile. Confirming our specific design goals, the Sidekick persona was perceived as lowest on Extraversion and highest on Neuroticism compared with other personas. The Buddy persona was perceived to be highly Extravert and Agreeable, and the Butler persona was perceived to be highly Conscientious and low on Neuroticism. We next statistically tested whether these *Trait Judgments* reflected our intentions when designing each persona.

We had specific predictions about persona differences for each trait (e.g., Buddy should be perceived as more Open than Butler and Sidekick, Sidekick more Neurotic than Buddy and Butler, etc.). In these and subsequent analyses, we therefore used standard statistical analysis methods for ANOVAs where the study had specific predictions. These statistical methods involve two phases: omnibus  $F$  tests followed by specific planned comparisons. For example, the omnibus tests indicated that there are overall differences between personas for Openness, but the planned comparisons are needed to determine whether predicted differences occurred between Buddy and Butler

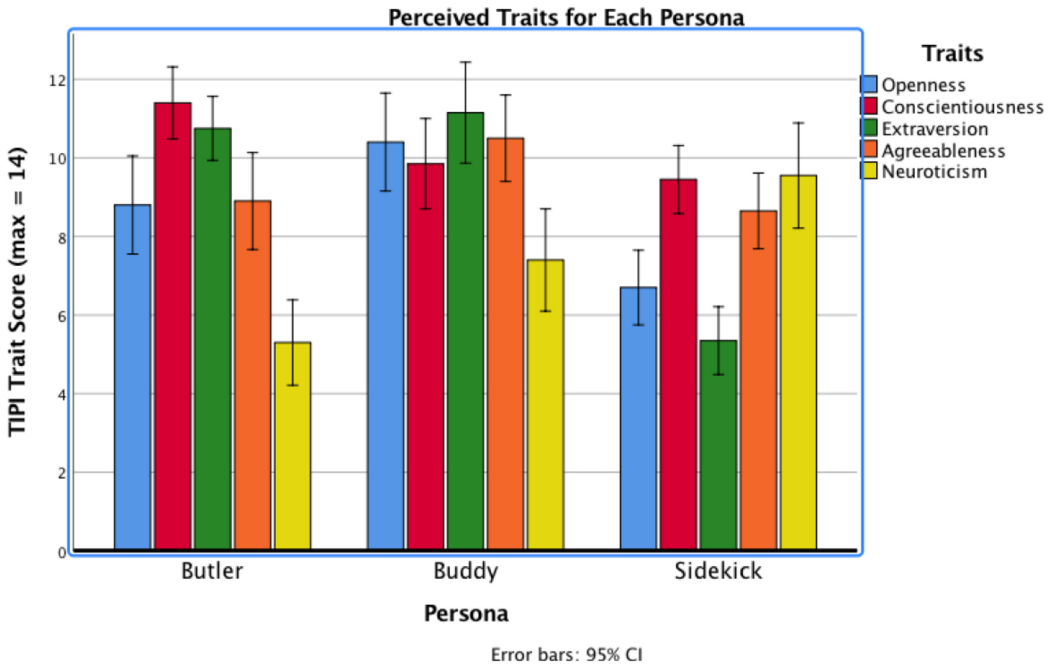


Fig. 7. Trait judgments for the different personas. Each persona was judged as possessing different traits. Butler is perceived to be highly Conscientious and low in Neuroticism, Buddy is perceived as Extravert and Agreeable, and Sidekick is perceived as more Neurotic and less Extravert.

and between Buddy and Sidekick. In each case, planned comparisons include corrections for multiple comparisons to address family-wise error, and analyses of effect sizes.

Following the persona design goals in Figure 2, we had the following expectations for each trait.

*Openness to Experience:* We anticipated that the Buddy persona would be judged as more Open than either the Butler or Sidekick personas. Planned LSD comparisons confirmed that Buddy was indeed judged as more Open than Sidekick ( $p = 0.001$ ) and Butler ( $p = 0.017$ ). Respective effect sizes were .29 and .47.

*Conscientiousness:* We anticipated that the Butler persona would be judged as more Conscientious than either the Buddy or Sidekick personas. Planned LSD comparisons showed that Butler was indeed judged as more Conscientious than Sidekick ( $p = 0.0001$ ) and Buddy ( $p = 0.015$ ). Respective effect sizes were .55 and .30.

*Extraversion:* We anticipated that the Sidekick persona would be judged as less Extravert than either the Butler or Buddy personas. Planned LSD comparisons showed that Sidekick was indeed judged as less Extravert than Butler ( $p = 0.0001$ ) and Buddy ( $p = 0.0001$ ). Respective effect sizes were .98 and .75.

*Agreeableness:* We anticipated that the Buddy persona would be judged as more Agreeable than either the Butler or Sidekick personas. However, planned LSD comparisons showed trending differences between Buddy and Butler ( $p = 0.064$ ) but not Sidekick ( $p = 0.744$ ). Respective effect sizes were .22 and .02.

*Neuroticism:* We anticipated that the Sidekick persona would be judged as more Neurotic than either the Butler or Sidekick personas. Planned LSD comparisons showed that Sidekick was indeed



judged as more Neurotic than Butler ( $p = 0.0001$ ) and Buddy ( $p = 0.003$ ). Respective effect sizes were .60 and .38.

**4.4.2 Preferences: People Prefer the Buddy Persona and Are Least Positive about Sidekick.** We next examined participants' overall preferences for the three personas (Butler, Buddy, or Sidekick). Participants showed clear preferences for the Buddy persona, with 16 of 20 participants ranking this most highly. The Sidekick persona was least popular; 15 participants liked it the least, with no one choosing it as their top preference. To test these preferences, we allocated a score of "2" to a top preference, "1" for second choice, and "0" for least favorite personality. There was a strong overall preference for Buddy over both Butler ( $t(19) = 3.022$ ,  $p = 0.007$ ,  $d = .34$ ) and Sidekick personas ( $t(19) = 7.069$ ,  $p < 0.00001$ ,  $d = .71$ ). The Butler persona was also preferred to Sidekick ( $t(19) = 3.579$ ,  $p = 0.002$ ,  $d = .42$ ).

Participants were then asked to justify their preferences. Although there was considerable variability in their explanations, key reasons for preferring the Buddy persona seemed to relate to his stimulating personality. Users commented that this personality was "enthusiastic," "energetic," and "upbeat." Against this, however, we also observed reservations about the Buddy persona, with two participants remarking that "positivity could get annoying" and "he was a bit too chirpy and friendly." In contrast, the Sidekick persona was least preferred because of his negative affect and apparently low confidence, with participants remarking, "I disliked that he was nervous" and "he sounded less animated and sad in the way he spoke." However, other participant observations about the Sidekick persona revealed quite complex emotional reactions. Sidekick Olly seemed to engender stronger emotional reactions than the other two personas, and people made comments such as "he's so cute." In contrast to the other personas, the majority of participants smiled or laughed when Sidekick Olly responded to the question of "how are you today" by simply responding he was "fine." A potential explanation for this was given by participant 20, who remarked "he is more human ... like in the sense of not being emotionally stable ... but not in a good way!"

Finally, Olly is presented as male, and we wanted to determine whether this influenced how he was perceived by participants of different genders. We therefore conducted a 2 (Participant Gender)  $\times$  3 Persona (Butler, Buddy, Sidekick)  $\times$  5 Trait (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) repeated-measures ANOVA, where Persona and Trait are within-subjects variables and Participant Gender is a between-subjects variable. The dependent measure was *Trait Judgment*. Participant Gender had no effects on Trait Judgments; there were no main effects of Participant Gender on Trait Judgments ( $F(1,18) = 1.46$ ,  $p = 0.24$ , partial eta squared = 0.08), nor did Participant Gender interact with either Traits ( $F(4,15) = 0.30$ ,  $p = .87$ , partial eta squared = 0.08) or Persona ( $F(2,17) = 0.28$ ,  $p = 0.76$ , partial eta squared = 0.03). Finally, there was no three way interaction between Participant Gender, Traits, and Persona ( $F(8,11) = .57$ ,  $p = .78$ , partial eta squared = .29).

**4.4.3 People's Ideal Robot Has Strong Positive Traits That Are Somewhat Emotionally Expressive.** Despite a clear preference for the Buddy persona, it may be that none of the personas we presented were consistent with how participants thought that Olly should interact. We therefore asked participants to specify their ideal Olly persona using the modified TIPI scale. The context for this question is that participants have recently interacted with three different personas, comparing them to choose their favorite and then justifying their choice. This would seem to provide good background information for making a judgment about an ideal persona.

Overall, results in Table 1 show that users generally want their Ideal Olly to express positive personality traits, with ideal traits for Conscientiousness, Agreeableness, Extraversion, and Openness being skewed to be highly positive (Means range between 10.558 and 12.601) and

Table 1. Ideal Olly Traits Emphasize Positive Attributes: People Want Highly Conscientious, Agreeable, Extravert, and Open Robots Who Are Low on Neuroticism (Maximum Score Is 14)

Trait	Ideal Olly Traits (Mean, SD)	Participants Self-Assessed Traits (Mean, SD)
Openness	10.55 (3.55)	10.20 (2.44)
Conscientiousness	12.60 (1.43)	10.30 (2.68)
Agreeableness	11.40 (2.62)	8.25 (2.59)
Extraversion	10.75 (2.34)	9.10 (2.17)
Neuroticism	4.25 (1.55)	6.90 (2.65)

Neuroticism being low (Mean 4.259). Nevertheless, while participants' Ideal Olly is low on the negative trait of Neuroticism, it is noteworthy that they didn't want this trait to be zero. In other words, people wanted a moderate amount of emotional expressivity and variability in their robot. To compare between ideal traits, we conducted a 5 Trait (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) repeated-measures ANOVA. The dependent measure was *Trait Judgment*. We found overall differences between traits ( $F(4,16) = 80.857, p = 0.000001$ , partial eta squared = .953). Post hoc LSD tests showed that Conscientiousness was more highly rated than all other traits (all  $ps < 0.027$ ), and Neuroticism the lowest ranked trait (all  $ps < 0.00001$ ).

We next analyzed whether people's Ideal Olly differed from the three personas we presented. We conducted a 4 Persona (Butler, Buddy, Sidekick, Ideal)  $\times$  5 Trait (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) repeated-measures ANOVA, where Persona and Trait are within-subjects variables. The dependent measure was *Trait Judgment*. The analysis showed a main effect for Personas ( $F(3,17) = 6.223, p = 0.005$ , partial eta squared = .523). Corrected LSD tests showed differences between Ideal and both Butler ( $p = 0.013, d = .18$ ) and Sidekick ( $p = 0.0001, d = .53$ ), but no overall differences between Ideal and Buddy ( $p = 0.850, d = .04$ ). This suggests that the Buddy persona is close to participants' ideal.

**4.4.4 People Prefer Robots Whose Traits Reflect Their Own Personality.** We also evaluated the extent to which people's ideal preferences are influenced by their own personality. Prior research is inconsistent here, with some studies showing preferences for a robot that is consistent with their own personality [45] and others showing a preference for a complementary personality [33, 39].

For each of the Big Five traits, we examined relations between participants' *Ideal Traits* for Olly and their *Self-Assessed traits*. Overall, people want their Ideal Olly to reflect their own personality. Across the different traits, correlations were significant and positive for Openness ( $r(18) = .533, p = .016$ ), Conscientiousness ( $r(18) = .473, p = .035$ ), and Extraversion ( $r(18) = .463, p = .040$ ), and trending for Agreeableness ( $r(18) = .380, p = .098$ ). However, there was no relationship between ideal robot and user personality for Neuroticism ( $r(18) = -.019, p = .936$ ). Overall, participants seemingly wanted their ideal robot to resemble themselves. Of course, as Table 1 shows, this ideal robot is an accentuated version of their own positive traits. This is confirmed by paired  $t$  tests showing that participants' ideal robot personality was more extreme for the traits of Conscientiousness ( $t(19) = 4.35, p < 0.0001, d = .49$ ), Extraversion ( $t(19) = 4.34, p < 0.0001, d = .48$ ), Agreeableness ( $t(19) = 3.81, p < 0.001, d = .43$ ), and Neuroticism ( $t(19) = 3.82, p < 0.001, d = .43$ ), but not for Openness ( $t(19) = 0.54, p < 0.60, d = .06$ ).

**4.4.5 Cues and Personality: Speech Is the Strongest Personality Cue but This depends on the Persona.** We next examined how different cues affected judgments participants made about

Table 2. Judgments of the Utility of the Different Motion, Color, and Speech Cues for Each Robot Persona (in General Cues Are Judged to Be Useful)

Persona	Cue Type	Mean Judged Cue Utility (1 = “of very little use” and 10 = “extremely useful”)
Butler	Motion	6.11
	Color	6.22
	Speech	7.33
Buddy	Motion	7.06
	Color	6.33
	Speech	8.11
Sidekick	Motion	6.22
	Color	5.00
	Speech	6.89

Olly’s personality, assessing the relative influence of verbal behavior, lights, and movement cues. Recall that after completing the survey for each persona, we asked participants to state how strongly each expressive cue (speech, color, and movement) affected their perceptions of Olly’s personality. We asked participants to rate cue strength on a scale of 1 to 10 with “1” being “very weak indicator” and “10” being “very strong indicator.” We called these *Cue Utility Judgments*.

These cuing judgments are shown in Table 2. With one exception, cues are judged to be medium to strong indicators of personality. Only the color cue for Sidekick was judged as not being significantly greater than the score of “5,” indicating that cue was “neither a strong or weak indicator of personality.”

However, we also wanted to know which cue participants judged most strongly indicated traits as well as whether such cues judgments varied across the different robot personas. We therefore conducted a 3 Persona (Butler, Buddy, Sidekick)  $\times$  3 Cue Type (Color, Motion, Speech) repeated-measures ANOVA. Both robot and cue type were within-subjects factors, and *Cue Utility Judgment* was the dependent variable. There was an overall effect of Robot Persona ( $F(2,16) = 4.157, p = .035$ , partial eta squared = .342), and Cue Type was trending ( $F(2,16) = 2.962, p = .080$ , partial eta squared = .270). There was no interaction between Robot and Cue type. When we compared the utility of the different cues, using LSD tests, speech was judged to offer a stronger personality cue than Color ( $p = .023, d = .17$ ), with no differences between other Cue types. Also, cues for Buddy were judged to be stronger than for either Butler ( $p = 0.03, d = .14$ ) or Sidekick ( $p = 0.04, d = .11$ ).

To examine these observations further, we looked at participants’ explanations of their choices and the extent to which these referenced the different cues. Preferences between personas were influenced by the speech, color, and movements of the different personas. Users drew attention to colors and tone of voice of the Buddy persona in motivating their preferences, and were very sensitive to differences in speech styles between personas, making reference to intonation, conversational style, and affect in speech:

[commenting on the Buddy persona] I liked ... the bright colors such as the pink.  
With my least favorite version [Sidekick], I noticed [Olly’s voice] sounded much lower and sad in the way he spoke in short answers.

Another user observed how Olly’s movements and conversational style influenced her preferences, pointing to how those movements affected her mood and suggestive interactive possibilities. She also felt that the Sidekick persona failed to engage her emotionally.

The [Buddy] version used lively motions to make me happy, and it was also more chattable. The [Sidekick] version feels a little bit cold and uncaring.

Other users focused solely on movement in choosing between the different personas, while noting the motivational characteristics of the inferred personality:

[The Buddy persona] was ... the kind of thing you need to hear in the morning. He made great gestures which replicated the music which was quite cool.

These descriptions were also striking in their use of anthropomorphic language in making choices. Here different Olly personas are described as “gregarious” or in other cases using “soporific” language that was “boring.”

[Olly being] gregarious in tone made conversation easy and the movement was reflective of a dynamic relationship, whereas the [Sidekick] robot was soporific in tone and sounded very boring.

*4.4.6 Informal Behavioral Observations.* The researcher also observed participant behaviors and comments about Olly, which were noted after each interaction. An explicit check question in the survey indicated that none of the participants realized that Olly was being controlled by the researcher, instead believing that they were directly interacting with the robot. This was also evidenced by behavioral data; informal analysis of researcher notes indicated that if there were technical issues, for example, Olly was slower than expected in responding, participants would ask again, try to rephrase the question, or encourage him into responding. Furthermore, many participants spoke to Olly as they would when speaking to an animal or small child: raising their voice, speaking slower, and using encouraging language, thus demonstrating elements of anthropomorphism. Participants also adjusted their own behaviors when interacting with Olly, sometimes synchronizing with his actions. They moved towards Olly while talking and smiled while he spoke, keeping their gaze on him for most of the interaction, suggesting they found the experience engaging.

## 5 DISCUSSION

We evaluated a hybrid cueing approach to robot personality by assessing user evaluations of a social robot. We signaled personality by combining both abstract cues (color and movement) with spoken behaviors that emulated standard human interaction. Following [11, 15], we exploited these hybrid cues to design three distinct personas that aimed to differ in proactivity and the extent to which they stimulated the user. After a short interaction with each of the three personas, we found that people judged the personas to be different in ways that largely reflected our design intentions, perceiving our Sidekick as Neurotic and low in Extraversion; Buddy as Extravert, Open, and Agreeable; and Butler as Conscientious. While many prior studies have focused on the Extraversion trait [2, 33], we confirm [31] in showing that participants are sensitive to other personality traits. Consistent with other work on non-anthropomorphic objects, we confirm that participants seem sensitive to quite abstract behavioral cues, involving movement [11, 17, 32, 58, 61]. Furthermore, these cues were usually interpreted consistently with our design intentions. Nevertheless, cues were differently effective, with speech cues seeming to be more effective trait indicators compared with colors and movement. It may be that people need more experience with such abstract cues in order to successfully interpret personality. We were largely successful in projecting different traits through cueing, with our trait predictions being largely confirmed for each persona. One exception, however, was for Agreeableness, where the predicted persona differences failed to

emerge. Work on human personality suggests that certain traits are more difficult for people to detect [22], and it may be that different cues are needed to project Agreeableness.

People also had clear preferences between the three robot personas, with a strong preference for the Buddy rather than the Sidekick or Butler personas. However, informal comments suggest there may be individual differences at play, with some users being intrigued by the understated aspects of Sidekick, and others being actively engaged by Sidekick's indirect interactive style. We also examined these preferences at the trait level by probing people's ideal robot traits. Here we confirm prior work [31] in finding a strong overall preference for positive personality traits, such as Openness, Extraversion, and Agreeableness, with Conscientiousness being the highest-rated trait. Neuroticism was also rated lowest. Nevertheless, users did not select positive traits unilaterally across the board; confirming [16], people wanted their ideal robot to be a little Neurotic, in other words showing some emotional expressivity. But despite this overall bias towards positivity, people's preferences were also influenced by their own personality. People want a robot that mirrors their own personality for all traits except Neuroticism. These findings extend prior work that examined this question for a single trait [2, 6, 39].

### 5.1 Design Implications

Overall, our study confirms other work [11, 17, 32, 40, 58, 61] that it's possible to design a non-anthropomorphic robot that is engaging to users. Furthermore, a robot does not have to be designed to exactly mimic human behaviors for it to be perceived as having a specific persona; our users attributed different traits in part by interpreting quite abstract behavioral cues (e.g., color and movement). The success of our design was also supported by the fact that people were also able to distinguish between, and express preferences for, different overall robot types that were complex combinations of traits (Butler, Buddy, Sidekick). People had clear preferences between both expressive robot personas and their underlying traits, in general wanting Buddy-style robots as well as those that have positive traits. Furthermore, our design approach is generative: new robot types can be defined to target different constellations of personality traits, and this study begins to specify how these traits can then be mapped to the expressive dimensions of color, movement, and speech. While human-like cues seemed to be more powerful in this study, our results nevertheless suggest that color and movement may also communicate personality traits.

In addition to discovering general preferences for positive traits and specific personality types, we also found that expressive robot designs may need to be customized to users' individual personality; people want expressive robots that reflect their own traits, although ideal robots should have more extreme traits than their users, as indicated by analysis of Table 1 data, showing differences between Ideal and participant personality for all traits except Openness. There are also other interesting design opportunities. For example, we know that participants are able to detect differences between personas, and it may be that users are interested in interacting with different personas in relation to different tasks, e.g., a more Conscientious Olly when doing the housework, but a more Agreeable one when relaxing [16]. There may be more general mappings between projected robot personality traits and task settings. For example, in many applications the robot's role is to assist the human with challenging or repetitive tasks. The Conscientiousness trait is associated with both organization and attention to detail, so users should judge a robot assistant demonstrating this trait as suitable for such tasks. Other tasks such as customer service demand social skills such as interpersonal warmth and empathy, where a robot demonstrating strong Agreeableness and Extraversion should be appropriate. For tasks requiring creativity, a robot that expresses Openness might be apposite. Tasks that would benefit from a Neurotic robot are less clear, but some of our participants found that Sidekick's emotional register made him more intriguing to interact with. A

common challenge with conversational robots is that their responses are seen as predictable and stereotyped, but it may be that unexpected emotional responses would elicit interest.

Finally, our work suggests design opportunities for enhancing speech-enabled home robots. Currently Amazon Alexa and Google Home are simple speakers that do not move and are visually somewhat characterless. User responses to our designs suggest interesting new possibilities for personality-enabling these devices by adding communicative color displays or by adding novel visual behaviors. Such visual behaviors could include showing “attention” and “interest” by orienting towards or away from the user, as well as “resting” behaviors communicating the robot’s internal state.

## 5.2 Limitations

One obvious limitation of this work is that user interactions with Olly were relatively short and rather constrained. In future work, we intend to move beyond scripted dialogues. Another limitation is that all participants were exposed to the different robot personalities in a fixed order, and it may be that habituation effects might explain why the Shy personality type was least popular. This study also tested the impact of many different cues in combination, and future work might explore individual impacts of one cue versus another, e.g., evaluating the accuracy of trait perception from speech alone versus colors alone, or comparing the effects of “orienting” versus “resting” behaviors. More targeted studies may be especially helpful in informing the design of abstract cues such as color or movement. Also, our evaluation of the strength of speech, color, and movement cues depended on participants’ conscious judgments, but it may be that these cues have unconscious effects that might require behavioral methods to detect. A final limitation is that Olly’s gender was presented as male. This may have affected our results as people may react differently to robot personas based on gender. In other words, participants may interact differently with a male versus female Buddy or a male versus female Sidekick. Our results showed, however, that participant gender did not affect how personas and traits were perceived.

## 5.3 Conclusions

We examine perceptions of, and preferences for, multiple robot personality traits combined in three composite personas for a voice-enabled home social robot. Confirming prior work, we found that people prefer a persona that complements their own personality and that possesses largely positive traits. At the same time our work confirms prior studies in suggesting that users can interpret quite subtle cues when making judgements about robot personality. Our findings also suggest that ideal robots don’t reflect the average human’s traits, in general being more extreme and more positive. We also find that quite abstract cues such as color may be useful for signaling complex aspects of a robot’s personality.

## REFERENCES

- [1] Lucy Anderson-Bashan, B. Megidish, H. Erel, I. Wald, Guy Hoffman, Oren Zuckerman, and A. Grishko. 2018. The greeting machine: An abstract robotic object for opening encounters. In *2018 27th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN’18)*, 595–602. IEEE.
- [2] Sean Andrist, Bilge Mutlu, and Adriana Tapus. 2015. Look like me: Matching robot personality via gaze to increase motivation. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 3603–3612.
- [3] Naomi S. Baron. 2015. Shall we talk? Conversing with humans and robots. *Inf. Soc.* 31, 3 (2015), 257–264.
- [4] Christoph Bartneck and Jodi Forlizzi. 2004. A design-centred framework for social human-robot interaction. In *13th IEEE International Workshop on Robot and Human Interactive Communication, 2004 (ROMAN’04)*, 591–594.
- [5] Jerome R. Bellegarda. 2013. Large-scale personal assistant technology deployment: The Siri experience. In *INTERSPEECH*, 2029–2033.
- [6] Emily P. Bernier and Brian Scassellati. 2010. The similarity-attraction effect in human-robot interaction. In *2010 IEEE 9th International Conference on Development and Learning (ICDL’10)*, 286–290.

- [7] Merel Brandon. 2012. Effect personality matching on robot acceptance: Effect of robot-user personality matching on the acceptance of domestic assistant robots for elderly. *MS thesis*. University of Twente.
- [8] Cynthia Breazeal. 2002. *Designing Sociable Robots*. MIT Press, Cambridge, MA.
- [9] Elizabeth Broadbent. 2017. Interactions with robots: The truths we reveal about ourselves. *Annu. Rev. Psychol.* 68 (2017), 627–652.
- [10] Justine Cassell and Kristinn R. Thorisson. 1999. The power of a nod and a glance: Envelope vs. emotional feedback in animated conversational agents. *Appl. Artif. Intell.* 13, 4–5 (1999), 519–538.
- [11] Jessica R. Cauchard et al. 2016. Emotion encoding in human-drone interaction. *11th ACM/IEEE International Conference on Human-Robot Interaction (HRI'16)*. IEEE Press.
- [12] Philip J. Corr and Gerald Matthews. 2009. *The Cambridge Handbook of Personality Psychology*. Cambridge University Press, Cambridge, UK.
- [13] Paul T. Costa Jr. and Robert R. McCrae. 1976. Age differences in personality structure: A cluster analytic approach. *J. Gerontol.* 31, 5 (1976), 564–570.
- [14] Kerstin Dautenhahn and Aude Billard. 1999. Bringing up robots or—the psychology of socially intelligent robots: From theory to implementation. In *Proceedings of the 3rd Annual Conference on Autonomous Agents*, 366–367.
- [15] Kerstin Dautenhahn, Sarah Woods, Christina Kaouri, Michael L. Walters, Kheng Lee Koay, and Iain Werry. 2005. What is a robot companion—friend, assistant or butler? In *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005 (IROS'05)*, 1192–1197.
- [16] Christopher Dryer. 1997. Ghosts in the machine: Personalities for socially adroit software agents. *AAAI Fall Symposium*.
- [17] Hadas Erel, Guy Hoffman, and Oren Zuckerman. 2018. Interpreting non-anthropomorphic robots' social gestures. *Human Robot Interaction Conference*.
- [18] Terrence Fong, Illah Nourbakhsh, and Kerstin Dautenhahn. 2003. A survey of socially interactive robots. *Rob. Auton. Syst.* 42, 3–4 (2003), 143–166.
- [19] Jodi Forlizzi. 2007. How robotic products become social products: An ethnographic study of cleaning in the home. In *Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction*, 129–136.
- [20] Jodi Forlizzi and Carl DiSalvo. 2006. Service robots in the domestic environment: A study of the Roomba vacuum in the home. In *Proceedings of the 1st ACM SIGCHI/SIGART Conference on Human-Robot Interaction*, 258–265.
- [21] Adrian Furnham. 1990. Faking personality questionnaires: Fabricating different profiles for different purposes. *Curr. Psychol.* 9, 1 (1990), 46–55.
- [22] Adrian Furnham. 2008. Relationship among four Big Five measures of different length. *Psychol. Rep.* 102, 1 (2008), 312–316.
- [23] Alastair J. Gill and Jon Oberlander. 2002. Taking care of the linguistic features of extraversion. In *Proceedings of the Annual Meeting of the Cognitive Science Society*.
- [24] Jennifer Goetz and Sarah Kiesler. 2002. Cooperation with a robotic assistant. In *ACM Conference on Computer Human Interaction*.
- [25] Lewis R. Goldberg. 1981. Language and individual differences: The search for universals in personality lexicons. *Rev. Personal. Soc. Psychol.* 2, 1 (1981), 141–165.
- [26] Lewis R. Goldberg. 1993. The structure of phenotypic personality traits. *Am. Psychol.* 48, 1 (1993), 26.
- [27] Samuel D. Gosling, Sei Jin Ko, Thomas Mannarelli, and Margaret E. Morris. 2002. A room with a cue: Personality judgments based on offices and bedrooms. *J. Pers. Soc. Psychol.* 82, 3 (2002), 379.
- [28] Samuel D. Gosling, Peter J. Rentfrow, and William B. Swann Jr. 2003. A very brief measure of the big-five personality domains. *J. Res. Pers.* 37, 6 (2003), 504–528.
- [29] Jasmin Grosinger, Federico Pecora, and Alessandro Saffiotti. 2016. Making robots proactive through equilibrium maintenance. In *Proceedings of the 25th International Joint Conference on Artificial Intelligence (IJCAI'16)*, Gerhard Brewka (Ed.). AAAI Press, 3375–3381.
- [30] Jonathan Grudin. 2006. Why personas work: The psychological evidence. *Pers. Lifecycle* 3, 3 (2006), 642–663.
- [31] Bram Hendriks, Bernt Meerbeek, Stella Boess, Steffen Pauws, and Marieke Sonneveld. 2011. Robot vacuum cleaner personality and behavior. *Int. J. Soc. Robot.* 3, 2 (2011), 187–195.
- [32] Guy Hoffman. 2012. Dumb robots, smart phones: A case study of music listening companionship. In *2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication*, 358–363.
- [33] Katherine Isbister and Clifford Nass. 2000. Consistency of personality in interactive characters: Verbal cues, non-verbal cues, and user characteristics. *Int. J. Hum. Comput. Stud.* 53, 2 (2000), 251–267.
- [35] Oliver P. John, Laura P. Naumann, and Christopher J. Soto. 2008. Paradigm shift to the integrative big five trait taxonomy. *Handb. Personal. Theory Res.* 3, 2 (2008), 114–158.
- [36] Zayera Khan. 1998. Attitudes towards intelligent service robots. *NADA KTH, Stock.* 17 (1998), 43–63.

- [37] Sara Kiesler and Jennifer Goetz. 2002. Mental models of robotic assistants. In *CHI'02 Extended Abstracts on Human Factors in Computing Systems*, 576–577.
- [38] Hyun Young Kim, Bomyeong Kim, and Jinwoo Kim. 2016. The naughty drone: A qualitative research on drone as companion device. In *Proceedings of the 10th International Conference on Ubiquitous Information Management and Communication (IMCOM'16)*. ACM, New York, NY, Article 91, 6 pages. DOI: <https://doi.org/10.1145/2857546.2857639>
- [39] Kwan Min Lee, Wei Peng, Seung-A. Jin, and Chang Yan. 2006. Can robots manifest personality?: An empirical test of personality recognition, social responses, and social presence in human–robot interaction. *J. Commun.* 56, 4 (2006), 754–772.
- [40] Michal Luria, Guy Hoffman, Benny Megidish, Oren Zuckerman, and Sung Park. 2016. Designing vyo, a robotic smart home assistant: Bridging the gap between device and social agent. In *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN'16)*, 1019–1025.
- [41] Charlotte Massey, Sean TenBrook, Chaconne Tatum, and Steve Whittaker. 2014. PIM and personality: What do our personal file systems say about us? In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 3695–3704.
- [42] Robert R. McCrae and Paul T. Costa. 1987. Validation of the five-factor model of personality across instruments and observers. *J. Pers. Soc. Psychol.* 52, 1 (1987), 81.
- [43] Albert Michotte. 1962. *The Perception of Causality*. Methuen, Andover, MA.
- [44] Youngme Moon and Clifford Nass. 1996. How “real” are computer personalities? Psychological responses to personality types in human-computer interaction. *Commun. Res.* 23, 6 (1996), 651–674.
- [45] Clifford Nass and Kwan Min Lee. 2001. Does computer-synthesized speech manifest personality? Experimental tests of recognition, similarity-attraction, and consistency-attraction. *J. Exp. Psychol. Appl.* 7, 3 (2001), 171.
- [46] Clifford Nass and Youngme Moon. 2000. Machines and mindlessness: Social responses to computers. *J. Soc. Issues* 56, 1 (2000), 81–103.
- [47] Laura P. Naumann, Simine Vazire, Peter J. Rentfrow, and Samuel D. Gosling. 2009. Personality judgments based on physical appearance. *Personal. Soc. Psychol. Bull.* 35, 12 (2009), 1661–1671.
- [48] James W. Pennebaker and Laura A. King. 1999. Linguistic styles: Language use as an individual difference. *J. Pers. Soc. Psychol.* 77, 6 (1999), 1296.
- [49] John Pruitt and Tamara Adlin. 2006. The persona lifecycle: Keeping people in mind throughout product design (interactive technologies). Morgan Kaufmann, MA.
- [50] John Pruitt and Jonathan Grudin. 2003. Personas: Practice and theory. In *Proceedings of the 2003 Conference on Designing for User Experiences*, 1–15.
- [51] Amanda Purington, Jessie G. Taft, Shruti Sannon, Natalya N. Bazarova, and Samuel Hardman Taylor. 2017. Alexa is my new BFF: Social roles, user satisfaction, and personification of the amazon echo. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, 2853–2859.
- [52] Byron Reeves and Clifford Nass. 2000. Perceptual bandwidth. *Commun. ACM* 43, 3 (2000), 65.
- [53] Byron Reeves and Clifford Ivar Nass. 1996. *The Media Equation: How People Treat Computers, Television, and New Media Like Real People and Places*. Cambridge University Press.
- [54] Yvonne Rogers and Paul Marshall. 2017. Research in the wild. *Synth. Lect. Human-Centered Informatics* 10, 3 (2017), i–97.
- [55] Duygu Sarikaya, Jason J. Corso, and Khurshid A. Guru. 2017. Detection and localization of robotic tools in robot-assisted surgery videos using deep neural networks for region proposal and detection. *IEEE Trans. Med. Imaging* 36, 7 (2017), 1542–1549.
- [56] Klaus Rainer Scherer. 1979. *Personality Markers in Speech*. Cambridge University Press.
- [57] Massimiliano Scopelliti, Maria Vittoria Giuliani, and Ferdinando Fornara. 2005. Robots in a domestic setting: A psychological approach. *Univers. Access Inf. Soc.* 4, 2 (2005), 146–155.
- [58] David Sirkin, Brian Mok, Stephen Yang, and Wendy Ju. 2015. Mechanical ottoman: How robotic furniture offers and withdraws support. In *Proceedings of the 10th Annual ACM/IEEE International Conference on Human-Robot Interaction*, 11–18. ACM.
- [59] Aaron Smith and Janna Anderson. 2014. AI, robotics, and the future of jobs. *Pew Res. Cent.* 6 (2014), 75–101.
- [60] Mark Snyder. 1983. The influence of individuals on situations: Implications for understanding the links between personality and social behavior. *J. Pers.* 51, 3 (1983), 497–516.
- [61] H. Tennent, S. Shen, and M. Jung. 2019. Micbot: A peripheral robotic object to shape conversational dynamics and team performance. In *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI'19)*, 133–142. IEEE.
- [62] Avril Thorne. 1987. The press of personality: A study of conversations between introverts and extraverts. *J. Pers. Soc. Psychol.* 53, 4 (1987), 718.



- [63] Michael L. Walters, Manja Lohse, Marc Hanheide, Britta Wrede, Dag Sverre Syrdal, Kheng Lee Koay, Anders Green, Helge Hüttenrauch, Kerstin Dautenhahn, and Gerhard Sagerer. 2011. Evaluating the robot personality and verbal behavior of domestic robots using video-based studies. *Adv. Robot.* 25, 18 (2011), 2233–2254.
- [64] Yingying Wang, Jean E. Fox Tree, Marilyn Walker, and Michael Neff. 2016. Assessing the impact of hand motion on virtual character personality. *ACM Trans. Appl. Percept.* 13, 2 (2016), 9.
- [65] Sarah Woods, Kerstin Dautenhahn, Christina Kaouri, R. Boekhorst, and Kheng Lee Koay. 2005. Is this robot like me? Links between human and robot personality traits. In *2005 5th IEEE-RAS International Conference on Humanoid Robots*, 375–380.
- [66] Stephen Yang, Brian Mok, David Sirkin, Hillary Ive, Rohan Maheshwari, K. Fischer, and Wendy Ju. 2015. Experiences developing socially acceptable interactions for a robotic trash barrel. In *2015 24th IEEE International Symposium on Robot and Human Interactive Communication (ROMAN'15)*. IEEE, 277–284.
- [67] James E. Young, Richard Hawkins, Ehud Sharlin, and Takeo Igarashi. 2009. Toward acceptable domestic robots: Applying insights from social psychology. *Int. J. Soc. Robot.* 1, 1 (2009), 95.

Received February 2019; revised August 2020; accepted September 2020