The Advisor Robot: Tracing People's Mental Model from a Robot's Physical Attributes

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ABSTRACT
Humanoid robots offer many physical design choices such as voice frequency and head dimensions. We used hierarchical statistical mediation analysis to trace differences in people's mental model of robots from these choices. In an experiment, a humanoid robot gave participants online advice about their health. We used mediation analysis to identify the causal path from the robot's voice and head dimensions to the participants' mental model, and to their willingness to follow the robot's advice. The male robot voice predicted impressions of a knowledgeable robot, whose advice participants said they would follow. Increasing the voice's fundamental frequency reduced this effect. The robot's short chin length (but not its forehead dimensions) predicted impressions of a sociable robot, which also predicted intentions to take the robot's advice. We discuss the use of this approach for designing robots for different roles, when people's mental model of the robot matters.

Categories and Subject Descriptors
H.1.2 [**Models and Principles**]: User/Machine Systems – *Human Factors, Software psychology*, H.5.2 [**Information Interfaces and Presentation**]: User Interfaces – *Evaluation/methodology, theory and methods,* I.2.9 [**Artificial Intelligence**]: Robotics – *Operator interfaces,* J.4 [**Social and Behavioral Sciences**]: Psychology.

General Terms
Design, Experimentation, Human Factors, Statistics.

Keywords
human-robot interaction, social robots, humanoids, dialogue, knowledge estimation, mental model, gender, perception

1. INTRODUCTION
Communication between people and interactive robots will benefit if people have a clear rather than befuddled mental model of what these robots can do, and if the mental models elicited by robots match their tasks [14,34]. Creating an unambiguous first impression of the robot's expertise and personality seems especially important for robots that will interact with strangers in public settings. Thus, a rescue robot should be strong but unthreatening. An advisor robot should be knowledgeable but approachable. This paper addresses how a robot's physical attributes create these important first impressions.

Fig. 1. The four robot heads used in the experiment.

Research on interpersonal interaction among people shows that people give off cues that influence others' first impressions of them through their facial features and voice. For instance, a person's facial symmetry is highly correlated with judgments of his or her attractiveness and intelligence [43]. Human faces also convey personality information. This information can affect decisions and can even create overconfidence in judgments [15]. For instance, a person whose voice has a low fundamental frequency will be viewed as particularly male and masculine. Nass and his colleagues [27] have shown that interactive technologies with differing voice fundamental frequencies convey strong impressions as well. In a study of a computer that talked, a voice with fundamental frequency of 110 Hz led to strong impressions of a male and a voice with fundamental frequency of 210 Hz led to strong impressions of a female; participants even conformed more with the "male" computer [27, pg 15].

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Ideally, new robot design should take advantage of the cues that will be given off by a robot's head and voice attributes. That is, the robot does not have to enumerate its personality and knowledge domains. Theoretically, we can create a robot that conveys its personality and expertise without instruction through the physical and interactive design of the robot. Interactive humanoid robots have a good start on creating a strong first impression because by virtue of their movement, appearance, and interactivity, they are more humanlike than other computer-based technologies. A humanlike form provokes automatic reminders of people. Interactivity in the form of speech, gestures, or purposive movements will prompt observers to anthropomorphize automatically, without any intent or thoughtful processing, e.g. [36].

2. THEORY OF MENTAL MODEL CREATION

Nass and his colleagues have argued that people apply stereotypes and social heuristics, and enact habitual social responses, with interactive systems automatically [27-29]. Consistent with their approach, there is considerable evidence for automaticity of social behavior in people [1]. The process underlying automaticity is bottom-up perception, that is, perception that occurs immediately and is often nonconscious.

We argue that a parallel cognitive process often occurs as well, involving structure mapping [12]. In structure mapping, our perceptions of an object, such as a smiling robot, trigger mental connections to similar or analogistic knowledge in long-term memory. These connections are the same type that cause people to think in terms of metaphors and analogies. In the case of the smiling robot, for example, viewers may be reminded of happy people (appearance similarity) or of a playful task (analogistic reasoning). Through exemplar-based or instance-based cognitive processing of the connections so triggered (e.g., [16]), a mental model emerges as a coherent persona or prototype of the robot. For example, the smiling robot might activate in the viewer's memory exemplars of the nonsocial category, *machines*, and of the social category, *nice people*, and perhaps of "nice" robots they have seen in movies. Combining these exemplars will lead to an integrated concept, such as *sociable robot*. We argue that through this process, robots' physical attributes can have a significant impact on people's mental models of robots and on people's responses to robots.

Why do we care about these cognitive elaborations? Phenomena such as stereotyping and anthropomorphism seem to arise automatically from perception. Although these phenomena will account for some initial social responses to robots, they may not account for all such responses. The mental model is people's representation of the robot and will help them impose structure and order on their observations of and interaction with the robot, especially when the robot's true nature is unknown, as is likely to be the case early in interaction. Understanding the elements and causal properties of the mental model of a robot can help us understand human-robot interaction at a deeper level. It will help us understand people's attributions and expectations, and mismatches between these expectations and robot behavior. We believe also that understanding people's mental models of a robot will help us to design the robot for the grounding process that must take place for effective human-robot interaction [19].

3. RELATED WORK

Today, comparatively little is known about the physical properties of humanoid and other anthropomorphic robots that lead to people's mental models of them. Most such robots reflect their designers' vision of the physical and interactive features that will provoke an appropriate mental model in users. Many researchers have carefully crafted the heads of their robots to match this vision. For example, AIBO has a dog's shape but a metallic and plastic skin. Far from cuddly, people who anthropomorphize AIBO do so not because of its looks but because of its purposive actions [11]. Noting that it did not feel like a dog, researchers who wished to investigate how real dogs would respond to AIBO dressed it in fur [21]. Leonardo is a robot at MIT whose appearance and expressiveness convey a more intimate vision [23]. This robot has a baby face, bunny ears, and fur reminiscent of a child's stuffed animal. The head is rounder than AIBO's is and has more expressiveness and facial features.

The Hug at Carnegie Mellon [13] and the Huggable at MIT [39] have a form designed specifically to evoke touch with a human. The Hug at Carnegie Mellon has a bulge that is suggestive of a head, to draw more attention to the outstretched arms offering a hug. By contrast, the MIT Huggable has the soft, furry face of a teddy bear. Robota is a robot designed to interact with children with autism, and is built on the form of a commercially available doll [35].

QRIO's face [40] was intentionally designed to look more machinelike than humanlike, so as to avoid the uncanny valley. More humanlike robot faces like Ulkni and Doldori [20] aim for expressivity based on the human face. Several android robots, such as Repliee R1 [25] are designed to look as much like a human as possible. Paro, a robotic seal, has a face and body specifically designed for therapeutic interactions with the elderly [42].

Some researchers have focused on the effects of voices. Nass et. al. [27,28] have conducted the most systematic studies on the social impact of synthetic voices in different contexts and with different users, although to our knowledge they have not studied voices in humanoid robots. Others have chosen a particular voice for their robot to represent its personality and to express emotion anthropomorphically. For instance, Breazeal and her associates adapted several key emotional attributes in human speech for the robot, Kismet [6]. In Japan, when the robot Robovie was used as an English tutor in a school, it was given a child's voice [18].

4. EMPIRICAL APPROACH

In this paper we took advantage of a reconfigurable robot head on a humanoid robot and its text-to-speech system to examine experimentally how the physical attributes of a robot's head and voice changed people's impressions of the robot, and whether these impressions influenced people's intention to take the robot's advice.

We used a statistical technique called mediation analysis [2,17,37] to identify the causal linkages in the experimental data between the physical attributes of the robot and the user's mental model of the robot, and between the mental model and people's intention to take its advice. The main goal of this research was to demonstrate the use of experimentation and statistical techniques to trace the origins of mental models of a humanoid robot. A secondary goal was to point to how we can make informed physical and interactive design decisions for creating robots appropriate for their tasks by understanding how these design decisions affect people's mental models of robots.

4.1 Hypotheses

In the experiment, a robot delivered health advice online. The robot was presented with one of its four reconfigurable heads, as shown in Figure 1. The head varied along two dimensions, length of forehead and length of chin. Otherwise, the large and wide eyes (whose size and distance apart can be varied), expressive eyebrows, moving lips, lip color, and other physical aspects of the head were the same across all four head conditions.

We chose to vary the forehead and chin dimensions for two reasons. First, prior research suggested that head length and width influence perceptions of a robot's humanlikeness [8]. Second, varying these dimensions of the head would allow us to examine the impact of the so-called baby face configuration, which in humans carries powerful cues to character and personality. The baby face is a round or oval head with small chin and large wide eyes. Perceptions of baby faced men are correlated with perceptions of their naivete, honesty, kindness, and warmth [4,44]. (Several humanoid social robots have had baby face-like heads: Leonardo from MIT, Pearl the Nursebot from CMU, Robovie-R from ATR, and LATTE from Sony.) To study the effects of a baby face versus mature face of a robot, systematically, we orthogonally varied the forehead and chin size of the robot. We hypothesized that the short chin would increase impressions of the sociability of the robot.

We also systematically varied the fundamental voice frequency of the robot, expecting that a higher frequency would be interpreted as female and a lower one as male. This manipulation builds on prior work. Nass has shown that voice cues, such as high versus deep voices, or introverted versus extroverted voices convey powerful social information about interactive technologies [27,28]. As we noted above, Nass has shown that people not only attribute gender to computer-generated voices at the male and female fundamental frequency but they also generalize these perceptions to gender stereotypes. As well, we recently showed that people communicate with a gendered robot differently [34]. In telling a robot about dating norms, participants (especially women) explained less to the female robot about dating norms than to the male robot. We interpreted this finding to mean that people assumed the female robot knew more about dating than the male robot did (just as they assume women know more about dating norms than men do). If the female robot already knew about dating norms, it did not need as much explanation of dating norms as the male robot did.

We used four different voices for the robot, derived from Cepstral's Theta [22]. Two voices were the standard male voice and a standard female voice, available in Cepstral. We also created two additional voices by altering the fundamental frequency of the male and female voices. We gave the male voice a higher basic frequency and the female voice a lower frequency to make the voices more childlike and more gender neutral. We call this "dampening" the voices, since the purpose was to test the strength of the gender effect for gendered voices. We tested the hypothesis that the robot with a male voice (and less so, a dampened male voice) would seem more masculine than the robot with a female voice. Following the social psychology literature [10] and Nass, [27], we hypothesized that the robot with a male voice would also seem most knowledgeable and competent. This effect should be lower in the male dampened voice condition.

5. METHOD

We tested the predictions in an online experiment in which anyone over the age of 18 could participate. Participants watched two short videos of the robot. The robot give the participant general health advice, such as one might receive from a doctor. The robot's 2-minute monologue included information about liquid intake, exercise, and the body mass index. The advice was adapted from several health sources including [24,31,33]. A nursing professor reviewed the script for accuracy and phrasing.

5.1 Experimental Design

The experiment used a 4 X 2 X 2 between groups factorial design. The between-groups factors were chin height (short or long), forehead height (short or long), and voice gender (male, male dampened, female, and female dampened). Participants saw only one of four robot heads (see Figure 1), and heard only one of four voices.

We animated the physical robot face, and synchronized the lip movements to the speech. The robot displayed several different facial expressions, including a happy smile, an interested head tilt, and others. The facial expressions software was based on that used by GRACE, Valerie, and George, robots with animated faces on an LCD screen [38]. Then, the physical robot was videotaped against a white background.[1]

Fig. 2. The robot speaking with different facial expressions.

5.2 Procedure

Participants participated in the experiment through a website. They watched a video of the robot talking (see Figures 1-2), giving health advice to the viewer. The monologue was adapted from a more extensive dialogue in which the robot gives health advice adapted to the person's habits. The development of this script led to other experiments [34,39]. Those experiments used interactive dialogues with the same robot and scripting system.

The video of the robot giving advice was broken into two segments: first a 1¼ minute segment, and then a ¾ minute segment. Participants watched the first segment, which gave general advice about drinking water and exercising. For example, the robot said, "Your body needs exercise to stay healthy. Did

[1] Videos are at http://peopleandrobots.org/pubs/AdvisorRobot

you know that exercise may lower blood pressure if you exercise at least 1 hour a week?" After the first video segment, participants entered their height and weight, which was used to calculate the participant's body mass index (BMI) [31]. BMI is a simplified estimate of whether a person is underweight, overweight, or at an appropriate weight for their height. The BMI was presented on the screen as the second video segment played. In the second segment, the robot explained what the BMI means. The robot did not customize the advice to the participant's BMI, but explained all three categories of BMI – underweight, normal, and overweight. The robot began the segment with an example, saying "I'm four feet, six inches tall and weigh 200 pounds, so my body mass index is 48.2. I do need to lose some weight." The example robot BMI was higher than all but 3 participants' BMI.

After watching both video segments, participants completed a post-experimental survey. In addition to the measures of interest, the survey contained several questions to insure that participants watched and listened to the robot and did not game the online survey. Participants who gamed the system were removed. A simple algorithm detected incorrect answers to memory questions (39 entries incorrect), multiple entries by IP address (47 entries were accounted for by only 14 users), repetitive answers (14 users were dropped when more than 88% of the 34 scale questions were answered with, for example, all 1s), or filling it out too quickly (having a total time less than that required to both watch the videos and answer the questions). A total of 72 entries were dropped for gaming, and 32 of those gamed the survey in more than one way.

5.3 Participants

Ninety-eight legitimate participants participated online. They were anonymous; we did not ask for personal information except their email, which was used only for payment, and their height and weight, which the robot used to calculate the participant's BMI and to provide advice. They were recruited through several websites, one that was a Carnegie Mellon experiment list website, and a second that was a popular website for giveaways and simple surveys. Participants were paid a US$5.00 Amazon.com certificate.

Table 1. Scales and their reliability.

Scale	Items	Alpha*
Sociability	cheerfulness, friendliness, warmth, happiness, likable, sympathy, compassionate, gentle, tender, emotion, attractiveness	.93
Knowledge	competence, knowledge, intelligence, expert, reliability, usefulness, trustworthiness, likable	.92
Dominance	strong personality, assertive, dominant, dominance, power	.84
Humanlikeness	natural, humanlike, like a human, lifelike, moves like a human, has a mind	.85
Masculinity	masculine, manlike, not womanlike	.58
Machinelikeness	machinelike	NA

* Cronbach's Alpha is a measure of the reliability of the scale as a whole. Alpha ranges from zero to 1.0 (highest).

5.4 Measures

On the post-experiment survey, participants rated the robot on 34 different Likert-type items, which were then combined into 6 scales following factor analysis and reliability checks. All items were drawn from previous research, such as [3]. The six scales and their component questions are shown in Table 1.

Table 2 shows the simple correlations among the scales.

Table 2. Simple correlations among dependent variables.

#	Dependent Variables	1	2	3	4	5	6	7
1	Robot gender	1.0						
2	Humanlikeness		1.0					
3	Machinelikeness		-.23	1.0				
4	Robot knowledge	.11	.61		1.0			
5	Robot sociability		.59	-.38	.57	1.0		
6	Robot masculinity	.70	.16	.18	.21		1.0	
7	Robot dominance		.12	-.18	.35	.35	.18	1.0
8	Will follow robot's advice (0 = no, 1 = yes)		.30		.36			.11

Note. N = 98. Correlations at or above .20 are statistically significant at the p < .05 level. Correlations less than r = .10 are not shown.

6. RESULTS

6.1 Manipulation Checks

To check on the validity of the voice manipulation, we asked participants if the robot was a male or a female. Although more participants thought the robot male than female, the differences by voice are highly significant (chi square 21.4, $p < .0001$). One hundred percent of the participants who heard the male voice said the robot was male; 95% percent of those who heard the dampened male voice said the robot was male; 73% of the participants who heard the dampened female voice said the robot was male, and 17% of the participants who heard the female voice said the robot was male.

We also asked the participants to suggest a name for the robot and coded these names as male or female using search engines and several websites identifying the gender and history of names [7]. We found the same pattern of results. Of participants who suggested a gendered name (half of the participants), 100% who heard the male voice suggested a male name, 88% of those who heard the dampened male voice suggested a male name, 70% who heard the dampened female voice suggested a male name, and just 35% of those who heard the female voice suggested a male name ($p < .01$). Finally, in Table 2 it can be seen that the participants' impression of the robot's gender was correlated highly with their ratings of its masculinity.

To check on the validity of the head manipulations, that is to check on whether the short chin created a baby face-like impression, we asked participants to tell us the age of the robot. Unfortunately some participants seemed to interpret this question in physical years since building the robot, whereas others interpreted it as though the robot were human – in all voice and face conditions, even when the voice was strongly manipulated to be an adult voice, some subjects rated the age as low as 2 years old (the range was 2 to 60). As an alternative, we examined answers to a check-off item asking participants if the robot was manlike, womanlike, girl-like or boy-like. A minority of participants, just 17%, thought the robot was girl-like or boy-like. More of those who saw the robot with a tall forehead thought the robot was manlike than those who saw the robot with a short forehead (72% tall forehead versus 45% short forehead), whereas ratings of child-likeness were just the opposite ($p < .02$). Chin size did not have significant effects across the four likenesses but the short chin increased ratings of the robot as womanlike (36% short chin vs. 19% long chin).

6.2 Direct Effects of Head and Voice

We next investigated the effects of the independent variables, chin and forehead size, and the robot's voice, on participants' intentions to take the robot's advice. We did not find any systematic effects of forehead size and thus, to simplify the results, we do not report further on this factor. We also do not report on other control variables that had little systematic difference. These include whether or not the participants used headphones and the participant's height and weight.

The ANOVA examining the effects of the two independent variables, chin size and voice, on whether or not the participants would take the robot's advice, showed voice to have a marginal effect and the interaction of voice and chin to be the most significant ($F = 3$, $p < .05$; see model 1 in Table 2). The interaction derives from the fact that the dampened voices muddled social responses. One hundred percent of the participants who saw the robot with a short chin and heard the robot speak in the undampened male voice said they would take the robot's advice. When the chin was long and had a male voice, or the voice was female and the chin was short, the percent went to 91%. The dampened voices lowered the percentages from 85% to 55%. Finally, only 50% of the participants who saw the robot with a long chin and heard it speak with a female voice said they would take its advice. Each of these four levels of response is significantly different at $p < .05$ using Student's *t* tests (which is appropriate for testing multiple individual differences).

6.3 Mediation Analysis

We argued that physical cues lead people to create a mental model of the robot. We conducted a mediation analysis to investigate the mental model. A mediation analysis identifies the variables that mediate, or explain, the effects of an independent variable on a dependent variable [2,17,37].

Generally, a variable may be said to function as a mediator to the extent that it accounts for the relation between the independent variable and an outcome of interest (the dependent variable). Mediators explain how external physical events or objects take on internal psychological significance [2]. For example, in another study we have hypothesized that a feeling of being respected mediates the effect of an adaptive robot dialogue on people's impression that the robot is an effective communicator [41].

We show a diagram in Figure 3 adapted from Baron and Kenny's influential paper on mediation. The model depicts a causal chain with three variables and two causal paths feeding into the outcome variable: the direct impact of the independent variable (Path c) and the impact of the mediator (Path *b).* There is also a path from the independent variable to the mediator (Path *a).*

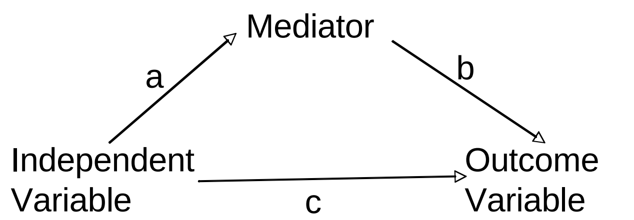

Fig. 3. Mediation model from Baron and Kenny [2].

A variable functions as a mediator when it meets the following conditions: (a) variations in levels of the independent variable significantly account for variations in the presumed mediator (i.e., Path c), (b) variations in the mediator significantly account for variations in the dependent variable (i.e., Path *b),* and (c) when Paths *a* and *b* are controlled, a previously significant relation between the independent and dependent variables is no longer significant, with the strongest demonstration of mediation occurring when Path *c* is zero. Typically, mediators significantly reduce Path *c* rather than eliminate the relation between the independent and dependent variables altogether. A significant reduction demonstrates that a given mediator is influential, though it may not be both necessary and sufficient for the effect to occur.

We apply this theoretical framework to the current study and to an understanding of mental models. Here, we are trying to identify variables associated with a mental model that explain the effects of voice and chin size on intentions to take the robot's advice.

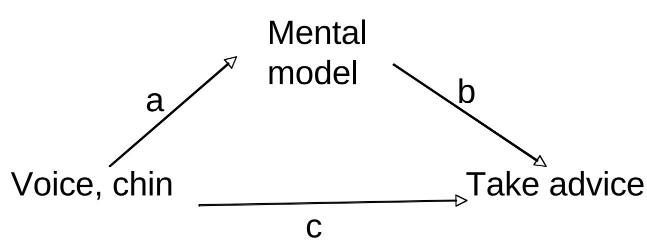

Fig. 4. Mediation model applied to this study.

Figure 4 shows the basic model with the mental model as a mediator. In reality, we explored several plausible mediators: the robot's humanlikeness, machinelikeness, masculinity, knowledge, sociability, and dominance (scales described in the Measures section).

To establish mediation, the mediators (in this case, dimensions of the mental model such as humanlikeness) are first put into an equation to see if they predict the dependent variable (intentions to take the robot's advice). Then, they are entered into the equation with the independent variables, voice fundamental frequency and chin size. If any of the potential mediators is actually mediating the link between the independent variables and the dependent variable, then they will be significant effects and they will reduce the effects of the independent variables on the dependent variable. The mediators take the place of the independent variable, showing that they are the closer cause of variation in the dependent variable.

Table 3. Hierarchical ANOVA mediation analyses predicting intentions to take the robot's advice.

Variables	Model 1	Model 2	Model 3
Short (vs. long) chin	n.s.	n. s.	n. s.
*Male (vs. female) voice	F = 2.4, p = .07	n.s.	n.s.
Chin X Voice	F = 3, p = .04	F = 2.4, p = .07	n.s.
Robot is humanlike		F = 3.8, p = .05	n.s.
Robot's knowledge			F = 5.6, p = .02
Robot's sociability			F = 2.2, p = .09
Robot's masculinity			n.s.
Robot's dominance			n.s.

Note. This analysis includes four voices in the male/female voice comparison (male, male dampened, female dampened, female).

Table 3 summarizes the results of the mediation analysis.

Model 1 in Table 3 shows the simple analysis of the positive effects of the male voice and head with a short chin on intentions to take the advice of the robot. We discussed this analysis above.

Model 2 of Table 3 shows the first mediation analysis, which asks if the attribution of the robot as humanlike mediates the influence of the physical cues. It does. The humanlikeness rating is significant and the influence of voice and the voice*chin interaction is reduced. This analysis indicates that impressions of humanlikeness are accounting for at least some of the reason why male voice and short chin size increased participants' intentions to follow the robot's advice.

Model 3 in Table 3 shows the next step in the mediation analysis. Here we are asking if perceived mental and personality attributes of the robot mediate the effects of its physical attributes or humanlikeness on participants' intentions to follow the robot's advice. The analysis shows that attributions of the robot as knowledgeable and, to a lesser extent, sociable, mediate the impact of its physical characteristics.

In Figure 5, we summarize graphically a slightly more extended version of the mediation analysis. The figure traces the causes of the participants' intentions to follow the robot's advice. At the bottom of the figure, to the right, we see that a short chin led participants to rate the robot as higher in sociability than if the robot had a long chin. A short chin also was negatively associated with rating the robot as machinelike (that is, the robot with the long chin was rated as more machinelike). When the robot was seen as more machinelike, it was rated as less humanlike. Viewing the robot as more humanlike led participants to rate the robot as more sociable and more knowledgeable. To the left, we see that the dampened male voice reduced the impact of the male voice. The regular male voice led participants to rate the robot as more masculine and more knowledgeable.

Finally, the chart shows that the greater the robot's knowledge and sociability, the stronger were participants' intentions to follow the robot's advice. Physical cues and robot humanlikeness are thus indirect causes of the robot's effectiveness.

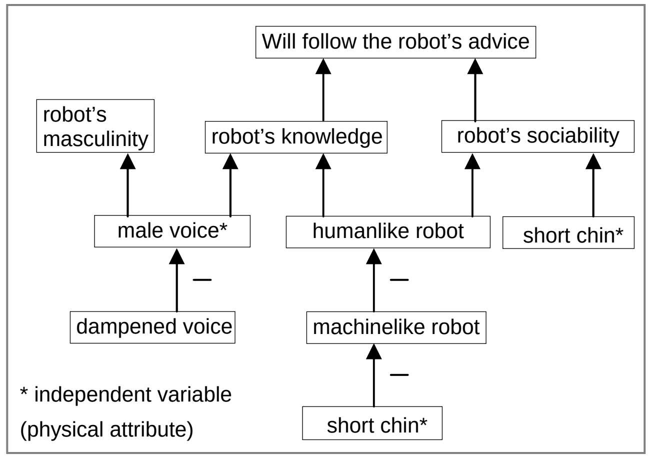

Fig. 5. Summary of sequential mediation analyses showing how physical features of the robot (chin, voice) lead to impressions that in turn lead participants to say they will follow the robot's advice.

7. DISCUSSION

Previous research has shown convincingly that humanoid robots (and other interactive technologies with humanlike characteristics) prompt automatic social responses in people [5,27]. Our research examines the cognitive mental model that accompanies these social responses. We show that the mental model is neither a mysterious black box nor a jumble of impressions and attributions. Instead, even in the first two minutes of observation, people create a coherent, plausible mental model of the robot. The mental model has similarity to people and machines, gender, and social and intellectual traits that are linked logically to one another and to the robot's credibility as an advisor. We show through hierarchical statistical mediation analysis how the physical attributes of the robot change the mental model, and how imputed traits of the robot represented in the model are linked causally to people's intentions. In this experiment, the robot's voice and physiognomy (reading traits from facial characteristics) changed people's perceptions of the robot's humanlikeness, knowledge, and sociability. In turn, perceptions of knowledge and sociability changed people's intention to follow the robot's advice.

As noted above, the effects of voice have been explored by Nass and his associates [27]. Our study points to the head and face as well. The shorter chin of the robot made the eyes a larger proportion of the face. (And the chin had a substantially large impact than the forehead.) Faces with large eyes and small chins in proportion to the rest of the face are called baby faced. Baby faced men are perceived to be more naive, honest, kind, and warm [4,44]. This research replicates this result with a robot. A baby faced robot's advice and recommendations may be followed more than a non-baby faced robot's advice.

7.1 Limitations

There are limitations to this work that include both validity and generalizability concerns. Validity concerns are whether we tested the hypotheses and accounted for alternative explanations of the results. With respect to validity, we did not collect individual data on participants' own characteristics. Thus we could not account for similarity effects, either personality similarity or voice similarity [28]. Subjects were randomly assigned to condition, but it is possible that the results are mainly due to extraverted people's responses. The robot's expressiveness and demeanor was comparatively extraverted (see Figure 2). The dialogue was outgoing, energetic, and forthright, for example, not hedging advice. Such a possibility does not invalidate the analysis method, but may be ignoring an important moderating process.

We can only speculate about the generalizability of our results. We did not test the viability of a mediation analysis of social responses to other interactive technologies, to nonhumanoid robots, or to humanoid robots with different physical attributes such as legs, arms, and more emotionality. Perhaps more important, the participants saw the robot in this experiment only through an online video. We speculate, with some justification in recent research [9], that, if the robot is physically present, people's mental model will be richer and less stereotypic than if the robot is presented online.

7.2 Future Work

An important avenue for future work is an examination of how differences in the mental model influence human-robot interaction over time, and how that interaction changes the mental model. Longitudinal hierarchical mediation analysis could be applied to that problem. That is, one would model how initial attributes in the mental model changed later interaction styles and later attributions, and as well, how aspects of interaction change the future mental model. In other work [19], we have argued that an interactive robot needs to create common ground with people. Common ground theory [32] suggests that this grounding process is significantly affected at the outset by physical features, especially when the robot's true nature is unknown or ambiguous. Physical features thus set expectations, but actual interaction involves an ongoing grounding process by which people (or people and robots) come to share mutual understanding. This understanding, in turn, will influence the mental model of the robot.

If we are interested in the mental model over time, the dialogue becomes a critical arena for research. Nass and Lee showed that the personality of the dialogue affected people's impressions of a computer [28]; they found that people gave better ratings to computers with voices whose extraverted or introverted personality matched their own. Moreno's research indicates that the personalization of an agent's dialogue has considerable impact [26]. In a personalized dialogue, a robot would use "I" and "you" as in informal conversation between people. Impersonal dialogue uses the third person. Nass and Brave [27] argue that personalized dialogue may be inappropriate for computer voices, but we speculate that just the opposite may be true of a humanoid robot.

Still another fruitful arena will be to explore how a robot can estimate individuals' knowledge, and adapt to their information needs. We have demonstrated that adaptation creates better information exchange and social impressions of the robot [41]. Considerable work must be pursued in the best ways for a robot to estimate individual differences and to behave in such a way to support a productive mental model in people.

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