First-Hand Impressions: Charting and Predicting User Impressions of Robot Hands

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Designing robotic hands has been an active area of research and innovation in the last decade. However, little is known about how people perceive robot hands and react to being touched by them. To inform hand design for social robots, we created a database of 73 robot hands and ran two user studies. In the first study, 160 online users rated the hands in our database. Variations in user ratings mostly centered on the perceived *Comfortableness*, *Interestingness*, and *Industrialness* of the hands. In a second lab-based study, users evaluated seven physical hands and had similar ratings to results from the online study. Furthermore, we did not find a significant difference in user ratings before and after the users were touched by the hands. We provide regression models that can predict user ratings from the hand features (e.g., number of fingers) and an online interface for using our robot hand database and predictive models.

CCS Concepts: • **Human-centered computing → Empirical studies in interaction design**; **Empirical studies in HCI**;

Additional Key Words and Phrases: Robotic hands, user experience, human-robot interaction, touch, user study

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1 INTRODUCTION

Hundreds of robotic hands have been designed in the last decades. For example, the humanoid robot, Pepper, has a five-fingered hand with articulated joints [9]. NAO uses a similar design but with only three fingers and no palm [1]. Other robots, such as the PR2 and Baxter, have metal grippers and/or suction cups [2, 5]. A growing number of soft manipulators are designed with novel materials and working principles [53]. For example, Homberg et al., developed a silicon-based pneumatic gripper that can comply with a wide range of object shapes [34]. New designs

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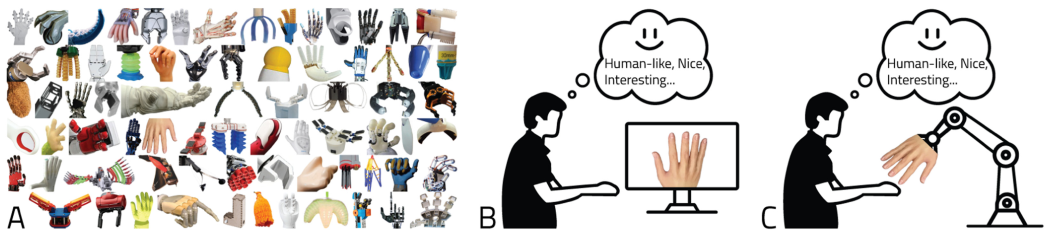


Fig. 1. Capturing user impressions of a diverse set of robot hands. (A) A collage of the 73 robotic hands in our database. (B) In an online study, users rated images of the robot hands. (C) In a lab-based study, users evaluated seven physical hands before and after being touched by the hands. User ratings showed similar trends between the online and in-lab settings and before and after touch.

appear every year focusing on dexterous manipulation of objects and performance metrics [13, 53].

Robotic hands are often used in collaborative settings with humans. For example, Baxter and PR2 can work on assembly and manipulation tasks with users [33, 48] or engage in social touch (e.g., hand clapping, hugging) [15, 27]. The soft gripper by Homberg et al., has been attached to Baxter and trained to grasp a range of household objects [34]. Socially interactive robots can use hand gestures or direct touch to convey emotion and intent in education, therapy, or service tasks [19, 23, 38, 45]. In these settings, users may merely observe the hand or interact with it through touch.

However, little is known regarding how people perceive different robotic hands, and how they respond to touch interactions with the hands. Despite the vast design space of robotic hands, little effort has been devoted to studying their design features (e.g., number of fingers) and how these features affect user impression. Recently, human-robot interaction (HRI) researchers have adopted online platforms such as Amazon Mechanical Turk for large-scale studies with users [39, 51]. Yet, we do not know if user perception of robot hands in an online study would be similar to a physical experiment where the robot hands are present in close proximity to the user. Furthermore, no data exists on how the user impressions may change if the hands contact the user's body. To support the increasing adoption of robots in social settings and guide the design of future robot hands, we set forth to answer the following questions:

- **RQ1. How do laypeople perceive subjective qualities of existing robot hands?**
- **RQ2. Do user ratings of the hands differ when collected online vs. an in-lab setting?** With this question, we investigate the impact of physical presence [18, 23] in evaluation of robot hands.
- **RQ3. Do user ratings change after being touched by the hands?** This question is motivated by past studies that suggest that touch interactions with a robot can improve user acceptance and behavior toward the robot [30, 54].
- **RQ4. What design features of the hands (e.g., number of fingers) can predict user ratings?**

To address these questions, we reviewed existing robotic hands and ran two studies to capture lay users' visual and touch experience with these hands (Figure 1). We first compiled a large set of robot hands from commercial and research venues and then selected 73 hands that represented the variations in the set. In an online study, 160 users evaluated images of the hands on 17 semantic differential rating scales. A principal component analysis of the ratings showed that three qualities of the hand *Comfortableness*, *Interestingness*, and *Industrialness* can describe variations in user ratings of the hands (RQ1). Next, we ran an in-lab study to further investigate if the in-person evaluation of the hands differ from the online results (RQ2) and how user evaluation of the hands is influenced by touch (RQ3). The participants rated seven prototype hands before and after receiving four short taps on their forearm from each hand. Our results did not show a statistically significant difference between user ratings of the hands in the lab and online. Also, we did not find a significant difference between the participants' ratings before and after the participants were touched by the robot hands. To inform the design of robot hands, we created a database of the 73 robot hands and coded their design features (e.g., number of fingers, color scheme). We trained 17 linear regression models to predict user ratings from the hand features. The shape of the fingertip, color scheme, and hand size were among the top predictors for most (≥14) of the regression models, while the visible surface texture, number of fingers, and existence of a palm only contributed to a few (≤3) predictions. We provide an online interface to the database and the predictive models and discuss implications of our findings for future work on robotic hands.

The contributions of the article are as follows:

- a database of 73 robot hands with 15 design features (e.g., number of fingers) and 17 user ratings (e.g., humanlike) per hand
- three subjective qualities (*Comfortableness*, *Interestingness*, and *Industrialness*) that describe variations in user ratings of robot hands
- comparisons of user ratings for robot hands based on images, physical hands in the lab, and physical hands after touch
- 17 regression models that can predict user ratings and an analysis of the models' most predictive design features
- the RobotHands online interface for browsing the database and predicting user ratings for new hands.[1]

2 RELATED WORK

We review the literature on designing robotic hands and present findings on user evaluation of robot appearance and robotic touch. In this article, we use robot "hand," "end effector," and "manipulator" interchangeably.

2.1 Designing Robot Hands

Existing robotic end effectors vary based on many design features. One of the earliest robotic hands was a two-fingered parallel jaw gripper that is still in use for many applications. Some designs closely replicated a human hand with articulated fingers and a palm [22] or were inspired by animals [40]. For example, similar to fish, some robotic end effectors use suction for grasping and moving objects [5]. Others may closely resemble a tool such as a cup holder or a hook [3]. The materials and working mechanisms of the hands have also evolved over the years. Early manipulators were composed of rigid parts and electrical motors [13]. Later efforts have incorporated soft elastic materials (e.g., electroactive polymers) in designing parts of the hand or the whole hand [53]. Soft manipulators tend to be smaller due to the actuation limitations of their materials [13]. Past studies have supported and evaluated the wide variety of hand designs according to performance considerations such as weight, speed, ease of design and control, and robustness in interacting with a wide range of objects [13, 53].

Human-robot interaction (HRI) researchers often use existing robot hands in their studies [33, 46, 54, 60]. As an exception, a few recent studies customized hands of commercial robots to improve user comfort in touch interactions with the robot. Fitter et al., placed boxing pads over the Baxter's

[1] http://robothands.org/.

grippers so that users can clap hands with the robot as part of their physical exercise games [28]. Zamani et al. designed a five-fingered flat hand for the Sawyer robot to study the impact of motion parameters (e.g., speed) on user evaluation of a robot-initiated tapping gesture [61]. The main motivation for designing a custom hand was to measure the applied force, but the authors also noted the addition of a silicone layer for user comfort. Another study used a similar design but with rubber pads instead of silicone [27]. These studies relied on the intuition of the researchers in their design and mainly focused on the material softness. We investigate how the materials and other design features of the hand can influence user ratings.

2.2 User Impression of Robot Appearance

People can form mental models of a robot and its capabilities based on its appearance [31, 42, 50, 55]. In a study by Powers and Kiesler, people perceived an anthropomorphic advisor robot with a short chin length to be more sociable, and they were more likely to follow its advice compared to a robot with a longer chin [50]. Li et al. compared a machine-like robot with an animal-like and a human-like robot in a study and found that the machine-like robot was less likeable than the other two robots [42].

Recent crowdsourced studies on large collections of social robots have found generalizable trends in user impressions of robots. Reeves et al. collected 300 social robots and showed that people evaluate and stereotype robots, similar to their impressions of humans, along two primary dimensions of warmth and competence [51]. Phillips et al. investigated the human likeness of 200 robots based on their images [49]. Kalegina et al. compiled a database of 176 robots with programmable faces and coded variations in their facial features (e.g., existence of eyelashes) [39]. Based on two studies with 12 and 17 robot faces, Kalegina et al. provided guidelines on how different facial features impact user ratings. These studies used images of the robots to collect user ratings on Amazon Mechanical Turk. Similarly, we use the Mechanical Turk to collect user ratings of a large set of robot hands. Our focus is on a single body part instead of the whole robot. Therefore, our database lists different types of hands for a robot (e.g., vacuum cup gripper and parallel jaw gripper for Baxter [5]) as separate entries. We also include hand prototypes that are not embedded in existing robots.

Many of the above studies investigated features that contributed to user ratings, but almost none provided a predictive model for user ratings. One exception is the work of Phillips et al., who developed a linear regression model for predicting the human likeness of robots. Phillips et al. included the model in an online tool together with their ABOT database [49]. Inspired by their work, here we present regression models for predicting user ratings of new robot hands and investigate the most predictive hand features for the models.

Finally, HRI researchers have proposed questionnaires for capturing the user impression of robots. The Godspeed questionnaire and the Robotic Social Attributes Scale (RoSAS) are the most frequently used instruments in the literature [11, 20]. The Godspeed questionnaire has 24 Likert-scale items that capture the user ratings of anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. The Godspeed questionnaire was developed based on a literature review of prior HRI questionnaires and related empirical studies, but the authors did not attempt to validate the Godspeed questionnaire. Later, Carpinella et al. developed the RoSAS and validated it in a series of online studies with descriptions of robots or images of robot faces. RoSAS is a 18-item questionnaire that captures the perceived warmth, competence, and comfort with a robot. These questionnaires capture user ratings of a robot, but the questions do not include any items about a robot's limb or user reactions to physical interactions with the robot. Thus, we used a custom questionnaire with items from the Godspeed and RoSAS questionnaires as well as additional items to capture user ratings of robotic hands and their emotions and comfort in physical interactions with the hands.

2.3 Touch Interactions with Robots

Past research suggests that physical interactions with a robot can impact user impressions and behavior toward the robot. Shiomi et al. showed that users rated a robot as friendlier, performed more actions, and spent more time on a repetitive task if the users touched the robot beforehand [44, 54]. The effect was even larger when the robot actively touched the participants back. Block et al. found that users felt more understood and trusted a robot more after receiving a hug from the robot [14]. A study by Fukuda et al. showed that receiving a touch from the robot during an unfair proposal in a game setting can inhibit the perception of robot unfairness [30]. To check if these findings hold for a robot limb, we tested whether user ratings of different hands changed after the hands touched the participants.

Others have investigated factors that influence acceptance and affective appraisal of a robotic touch. Chen et al. found that users had higher acceptance of a robot-initiated touch if the intent was instrumental (e.g., cleaning the participant's hand) rather than affective (e.g., providing comfort) [21]. Teyssier et al. studied how the type of touch (e.g., tapping) and its amplitude, force, and velocity are linked to the perceived pleasantness and intensity of touch [57]. Type of touch did not have a clear link to user ratings, whereas all the other factors influenced the ratings. Similarly, Zamani et al. varied parameters of a tapping gesture and found that force had a significant impact on arousal and dominance ratings [61]. Based on these findings, we used a tapping gesture with a preset force and velocity in our in-lab study.

While touch studies usually need physical contact, the literature suggests that users can infer some aspects of a tactile experience through vision. In particular, there is high correspondence between visual and tactile evaluations of material roughness and hardness [12, 58]. The same patterns hold for texture evaluation in the visual and tactile modalities [59]. Other studies showed that people can also visually infer affective qualities of materials and vibrations [29, 52]. In tactile HRI, a recent study found that user pleasantness ratings for videos of a stroking sensation peaked at 3 cm/s, similar to ratings of a physical stroking experience [60]. We reflect on results of our in-lab study in relation to this correspondence between visual and tactile evaluation.

3 STUDY I - THE PERCEPTUAL SPACE OF ROBOT HANDS

To investigate the perceptual space of robot hands (RQ1), we collected a representative set of 73 hands from industry and academia, designed a custom questionnaire, and ran an online user study on Amazon Mechanical Turk.

3.1 Compiling Representative Robot Hands

Collecting a Large Set of Hands. We use a broad definition for robot hands to capture a large variety of designs. Specifically, our definition includes robotic end effectors that can pick up, hold, or manipulate objects. We also include robot parts that are located at a place that is normally associated with a hand (e.g., end of a robot arm) or have the appearance of an animal or human hand. The first part of this definition covers the wide range of robotic grippers [53] and suction cups [5]. The second part covers hands with rigid designs such as those in the KASPAR [36] or the CuDDler [43] robots. We exclude robotic limbs that are only used for locomotion (e.g., [4]) as well as exoskeletons [16]. Also, we exclude graphical renderings of robot hands [32] or hands that are shown in animations or movies. This definition covers a wide range of designs that have the functionality or appearance of a hand but keeps the hand selection focused on existing physical designs.

Fig. 2. Example of an edited image in Study I. The image shows the PR2 gripper and its size w.r.t a medium-sized mug [2].

Using this definition, we collected 371 robot hands from existing robot databases and review papers. The authors examined all the robots in the following three databases: (1) IEEE Robots database [7] which has 232 robots, (2) Stanford Social Robot Collection [10, 51] with 342 robots, and (3) ABOT (Anthropomorphic roBOT) database [6, 49] with 251 robots. The second and third databases were recently developed by HRI researchers with the aim to compile a comprehensive collection of robots. We listed all the robots that had a hand according to our definition. If a robot had multiple hand designs (e.g., Baxter [5]), we added all the designs to our list. This led to 130, 124, and 85 unique hands from these three sources, respectively. Finally, we added 32 new designs by examining all the hands presented in recent review papers on robotic manipulators [13, 53].

Selecting Representative Designs. We chose 73 robot hands that captured the design variation in the larger set of hands. All four authors separately identified a subset of the 371 hands that the authors deemed to represent the variations in the appearance and working mechanisms of all the hands in the original set. In particular, we paid attention to the number of fingers, materials, rigid vs. moving parts, working mechanism, and colors of the hands. Next, the authors merged their choices in a meeting. We included all the hands selected by four (n = 10 hands) or three authors (n = 25). We discussed the hands selected by one or two authors and reached a consensus on which ones are distinct and should be included in the final set. We added 26 and 12 hands that were selected by two authors and one author, respectively.

Preparing Robot Hand Images. We divided the 73 hand models into 8 subsets and prepared their images for the study. One of the authors grouped the hands with an overall goal of having a variety of hand designs (e.g., number of fingers, colors) in each of the eight sets. Each set included the edited images of nine unique hands as well as the PR2 gripper for comparison [2]. For each robot hand, we prepared a single image with a white background showing the hand in one or two poses and included a mug or a coin as a scale reference (Figure 2). For the majority of the hands, we found one neutral open pose and one closed or figurative pose (n = 49 out of 73 hands). If one of these two poses was not available online (n = 5), we included two images from different angles (e.g., palmar and dorsal sides of the hand). If the hand was rigid (n = 13) or if only one pose was available online (n = 6), we included one image of the hand.

3.2 Designing a Custom Questionnaire

Since no established questionnaire exists for a robotic limb, we designed a custom questionnaire based on past studies of robot appearance and touch interaction. We also used a set of demographic questions from prior work.

Robot Hand Questionnaire. We aim to capture user impressions of a hand or a robot with this hand as well as user emotions and comfort in interacting with the hand. Our questionnaire has

17 semantic differential ratings on a 0–100 scale. While no consensus exists in the literature on the appropriate range for a rating scale, we use the 0–100 scale to regard the data as interval rather than ordinal in our analysis. Specifically, one can apply parametric statistical analysis methods (e.g., ANOVA, linear regression) to analyze the ratings on this scale. Our choice of scale is also in line with the prior studies on user ratings of robots [39, 49]. Ten of the ratings are about qualities of the hand (e.g., humanlike) or a robot with this hand (e.g., intelligent). Eight out of the ten ratings are from the Godspeed questionnaire [11], RoSAS [20], and a recent study on user perception of robot faces [39]. While a core principle of the Godspeed and RoSAS questionnaires is that of increasing internal reliability, using a large number of ratings from these questionnaires would incur increased study fatigue in the participants. Thus, we employed a subset of items from these questionnaires to capture user ratings of robots. The Creepy - Nice scale is from the IEEE Robots database [7]. We added the Boring - Interesting rating based on internal discussions. We also included three ratings to capture users' emotion(s) if the users are touched by the robot [17]. Past studies have used custom statements to assess user comfort in physical interactions with robots [21, 61]. Thus, we added four ratings to capture user comfort when touching the robot hand, being touched by the hand, passing or receiving objects from the hand, and being present near the robot hand. Similar to Kalegina et al. [39], we also asked respondents to provide a descriptive name for the hand and to indicate suitable jobs for it. Table 1 presents all the questions, their shorthand for the rest of the paper, and their literature references. We denote the shorthand that corresponds to the 17 user ratings with capitalization (e.g., Humanlike) in the rest of this article.

The questionnaire displayed the hands from one of the eight sets in a random order. Each page showed the edited image of a robot hand at the top and asked the participants to indicate if there is a robot hand and/or object in the image. Next, the participant answered the questions in Table 1 for that hand. As an attention test, we added an extra rating for two of the robot hands in the questionnaire and asked the participants to set its value to "very uncomfortable (0)". We also included a dummy blue image instead of a robot hand as an attention test.

Demographic Questionnaire. The demographic questionnaire asked about the participants' age, gender, and the country where they grew up. We also asked them to rate their familiarity with robots on the following scale: (1) None: I have no experience with robots; (2) Novice: I have seen some commercial robots; (3) Beginner: I have interacted with some commercial robots; (4) Intermediate: I have done some designing, building, and/or programming of robots; (5) Expert: I frequently design, build, and/or program robots. Finally, we used the Negative Attitude Toward Robots Scale (NARS) to capture variations between users in their beliefs and feelings toward robots [46, 47]. NARS has three subscales capturing negative attitudes toward interacting with robots (S1), social influence of robots (S2), and emotional communication with robots (S3). We included the first subscale from NARS (S1), as it was the most relevant for the evaluation of robot hands.

3.3 Running an Online Study

We administered the survey online through the Amazon Mechanical Turk. The criteria for eligible turkers were having more than 5,000 approved hits and a hit rate of 99% or more. The participants needed to confirm that they are 18 years or older, have normal or corrected to normal vision, and understand English at least at the B2 level. We recruited a total of 168 participants. We removed 8 participants who did not pass our attention tests, resulting in 20 responses for each of the eight sets.

The majority of the participants were from the United States (122), followed by India (15), Brazil (13), Italy (5), Canada (2), Australia (1), England (1), and Turkey (1). The participants self-identified as man ($n = 66$), woman (93), or nonbinary (1). The majority rated their familiarity with robots as novice (65) or beginner (57), followed by no familiarity (23), intermediate (11), or expert (4).

Table 1. The questionnaire used in the studies. The second and third columns show the acronyms we use for the user ratings in the rest of the paper and citations to the origin of the ratings/questions, respectively

Question	Shorthand	Reference
Give a descriptive name to the robot hand.	-	[39]
This robot hand is ...		
Machinelike - Humanlike	Humanlike	[11, 39]
Creepy - Nice	Nice	[7]
Boring - Interesting	Interesting	-
Incapable - Capable	Capable	[20]
Dangerous - Safe	Safe	[20]
A robot with this hand is ...		
Masculine - Feminine	Feminine	[39]
Childlike - Mature	Mature	[39]
Unfriendly - Friendly	Friendly	[11, 39]
Unintelligent - Intelligent	Intelligent	[11, 39]
Untrustworthy - Trustworthy	Trustworthy	[39]
If this robot touches me, I would feel ...		
Unhappy - Happy	Happy	[17]
Calm - Excited	Excited	[17]
Submissive - Dominant	Dominant	[17]
I feel [Uncomfortable - Comfortable] to ...		
Touch this robot hand.	To Touch	-
Be touched by this robot hand.	Be Touched	-
Pass or receive objects from this robot hand.	Handover	-
If this robot hand interacts with objects near me.	Nearby	-
Which jobs or roles will this robot be suitable for? (Select all that apply)	-	[39]
Education, Entertainment, Healthcare (nursing, rehabilitation), Home, Industrial (factory), Research, Service (hotel, restaurant, shops), Security (surveillance, security guard), Other (please specify)		

Similarly, the majority of the participants in each set rated their familiarity with robots as novice or beginner, followed by no familiarity, intermediate, or expert. The NARS scores were measured on a scale from 6 (the lowest) to 30 (the highest) for a negative attitude toward robots. The mean of the participant scores was 11.75 ($std = 4.88$), indicating positive to neutral attitudes toward robots.

3.4 Results

We present a low-dimensional perceptual space for the hands and summarize its correlations with the selected applications for the hands.

RQ1. How do laypeople perceive subjective qualities of existing robot hands?

We derived a perceptual space for the hands from the user ratings. The 17 rating scales showed strong correlations ($r(72) > .5$, $p < .0001$) for around 60% of the bi-variate correlations. Figure 3 presents the distribution of the mean user ratings for the 73 robot hands with example hands from the dataset that fall on the extremes of each rating scale. One can see a few hands (from the 73 in our dataset) fall at the extremes of several rating scales. To obtain a low-dimensional representation of user ratings, we applied Principal Component Analysis (PCA) to the average ratings for the robot

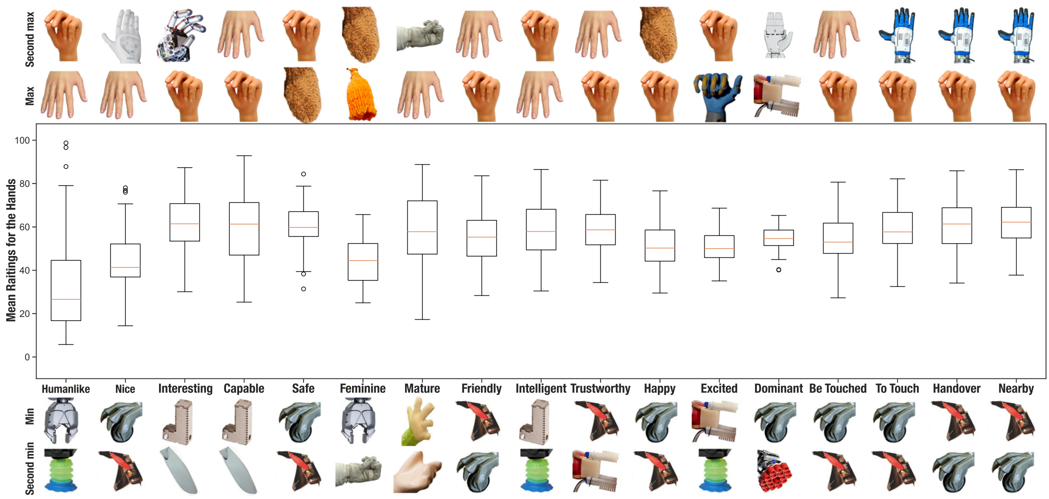


Fig. 3. Distribution of the mean user ratings for the 73 hands in the online study. We show the hand images with the highest (max), second to the highest (second max), lowest (min), and second to the lowest (second min) values on the rating scales.

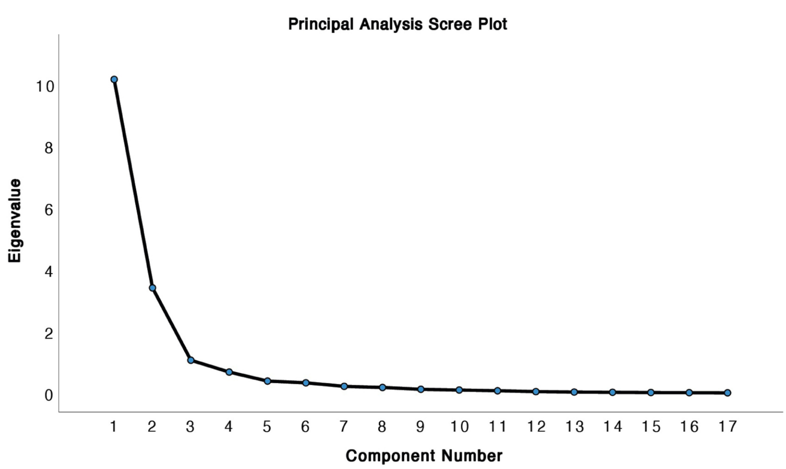


Fig. 4. Scree plot from principal component analysis (PCA) on the average user ratings on the 17 rating scales for the 80 hands. Three components have eigen values above 1.

hands. The PCA yields three dimensions (principle components) that had eigenvalues greater than 1 (Figure 4) and together explained 86.13% of the total variance (Table 2). Following the convention in the previous HRI studies [20, 49], we consider values higher than 0.5 as strong loadings and include them in the interpretation of the PCA components. After the Varimax rotation, the first dimension (or component) reveals strong loadings (>.50) for eleven ratings including user comfort To Touch, user comfort to Be Touched, Friendly, Safe, user feeling Happy, Trustworthy, Nice, user comfort to be Nearby, user comfort to Handover, user feeling Dominant, and Intelligent ratings. These ratings correspond to the positive feelings of comfort and safety in interacting with the hand. Thus, we label this dimension as *Comfortableness*. The second dimension has strong loadings for six ratings including Interesting, user feeling Excited, Intelligent, Capable, Humanlike, and Mature.

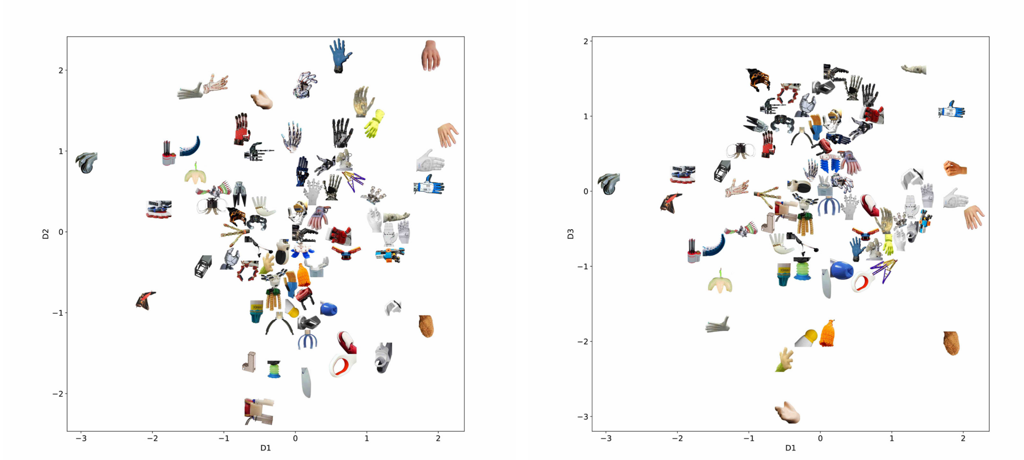
Table 2. Principal components loading matrix after varimax rotation. Loadings above 0.5 are in bold [20, 49]

Rating Scales	PC1 Comfortableness	PC2 Interestingness	PC3 Industrialness
[User comfort] To Touch	**.96**	.16	.06
[User comfort to] Be Touched	**.95**	.21	−.06
Friendly	**.94**	.19	.20
Safe	**.91**	.06	−.21
[User feeling] Happy	**.90**	.34	−.07
Trustworthy	**.88**	.38	.19
Nice	**.87**	.21	.16
[User comfort to be] Nearby	**.86**	.34	.31
[User comfort to] Handover	**.84**	.36	.33
[User feeling] Dominant	**.66**	−.23	−.25
Interesting	.30	**.82**	.22
[User feeling] Excited	−.07	**.82**	.11
Intelligent	**.51**	**.70**	.42
Capable	.41	**.66**	**.56**
Humanlike	.49	**.64**	−.24
Feminine	.26	−.04	**−.90**
Mature	.09	**.54**	**.74**
Eigenvalue	10.16	3.41	1.07
% Variance	59.75	20.08	6.30

These ratings correspond to the user interest and perception of the capability of the hand. We label this dimension as *Interestingness*. Dimension 3 has strong loadings for three ratings of Feminine, Mature, and Capable. Also, D3 has low (<.10) or negative loadings for user feeling Happy, user feeling Dominant, Safe, user comfort To Touch, and user comfort to Be Touched. In addition, the D3 values show a strong linear correlation with the number of times the participants selected "Industrial" as a suitable application category for each hand ($r(72) = .79$, $p < .0001$ - Figure 6). These loadings and the correlation result suggest a category of industrial hands that are capable of assembling objects, but they are not inviting users for touch interaction. Thus, we label this dimension as Industrialness, i.e., the quality or state of being industrial.

Figure 5 depicts these three dimensions with images of the robot hands. Moving from low to high values on D1 and D2 (i.e., bottom left to top right corner of Figure 5(a)), the hands increasingly resemble the human hand and have several fingers or joints. Interestingly, the bottom left corner of the space (i.e., low comfort and interest) is empty suggesting that the users found the hands either comfortable and safe or interesting. The majority of grippers and static hands have negative values on the *Interestingness* dimension (D2). The hands with positive values on D3 (i.e., *Industrialness*) have metal components, whereas those with negative D3 values have softer materials (e.g., silicon, plastic, and fur), bright colors, and/or a static or rigid configuration (Figure 5(b)).

Discussion. In the above PCA space, some of the 17 ratings load on more than one PCA dimension. For example, the Intelligent ratings have strong loadings (>.5) on two dimensions. In such cases, it is common to try alternative rotation methods (e.g., oblique rotation) to obtain a solution with the least cross-loadings and/or delete items that load on multiple dimensions. We applied various orthogonal and oblique rotations to the PCA solution. The obtained solutions from these methods had similar number of cross-loadings and only the items with the cross-loadings changed



(a) D1 and D2 denote Comfortableness and Interestingness of the hands, respectively.

(b) D1 and D3 denote Comfortableness and Industrialness of the hands, respectively.

Fig. 5. The four-dimensional representation of user ratings for the 73 robot hands from principal component analysis (PCA).

in the results. Thus, we decided to retain the Varimax solution that applies an orthogonal rotation to the PCA space and is commonly used in the literature. Furthermore, we decided to retain all the 17 rating scales since the purpose of this research is to chart the user ratings of robot hands and their similarities and differences with a low-dimensional space rather than developing a questionnaire for robot hands. Studies that focus on questionnaire development usually employ a large number of items (e.g., over 40) which can allow for better separation of the factors. Thus, we keep all the 17 ratings in the PCA solution to represent the contributions of all the ratings to the three resulting dimensions.

Suitable Application Categories for the Hands. To further chart user perception of the hands, we counted the number of times that the participants selected an application category for each robot hand. Figure 6 shows the correlations between the frequency of the selected applications for each hand and the hand positions on the three PCA dimensions. PCA dimension 1 (i.e., *Comfortableness*) has high positive correlations ($r(72) > .5$, $p < .0001$) with the frequency of selecting Education, Healthcare, Home, Service, and the total frequency of applications selected for the hands (i.e., All Applications). In other words, with an increase in the *Comfortablenss* of the hand (D1), the hands are perceived to be more suitable for these applications. PCA dimension 2 (i.e., *Interestingness*) has high correlations with Healthcare ($r(72) = .55$, $p < .0001$) and total number of applications for the hand ($r(72) = .52$, $p < .0001$). PCA dimension 3 (i.e., *Industrialness*) has high correlations with Industry ($r(72) = .79$, $p < .0001$) and Security ($r(72) = .57$, $p < .0001$) selections. This result suggests that people regard the hands with high masculine and mature ratings to be suitable for these applications.

4 STUDY II - THE IMPACT OF PHYSICAL PRESENCE AND TOUCH

Our next study examined whether the results of the online study are applicable to an in-person experience of robot hands (RQ2), and if the user ratings change after being touched by the hand (RQ3). To answer these questions, we prepared seven robot hand prototypes and collected user evaluations of them via online and in-lab experiments.

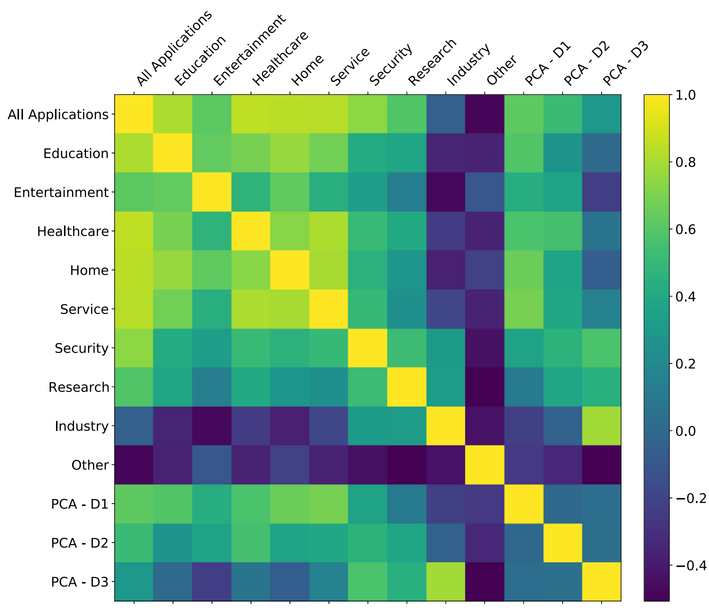


Fig. 6. Correlation matrix showing the relationship between the frequency of selected application categories and PCA dimensions.

Fig. 7. The seven hands used in Study II. (A) Existing robot hands with various design features from Study I. (B) The corresponding hand prototypes that we used in Study II. From left to right, we call the prototypes "human replica," "soft gripper," "furry hand," "metal skeleton," "hard gripper," "black plastic," and "suction cup" in our results.

4.1 Seven Robot Hand Prototypes

We chose seven distinct hands with different numbers of fingers, materials, and working mechanisms from Study I and prepared prototypes with a similar look and feel (Figure 7(A)). Three of the hands have five fingers resembling a human hand but with different materials (Hands 1, 4, and 6). We included two grippers, one with soft materials, three fingers, and a pneumatic actuation mechanism (Hand 2) and the other one with hard components, two fingers, and mechanical actuation (Hand 5). Finally, we included a static furry hand (Hand 3) and a suction cup (Hand 7).

Next, we prepared seven prototypes, aiming to make them similar to the selected hands in visual appearance and haptic properties (Figure 7(B)). For Hands 1, 3, and 7, we bought a silicon replica of the human hand used for jewelry display, a 40-mm Bellows Vacuum Suction Cup, and a teddy bear,

Fig. 8. The setup for the in-lab experiment. The left and right images show the *in-lab visual* and *in-lab touch* conditions, respectively. The participant's face is blurred to preserve anonymity.

respectively. We call these hands "human replica," "suction cup," and "furry hand" in the results. For Hand 2, we silicone-moulded the three fingers and the center cube, 3D printed the base, and attached plastic tubes to the fingers. We call this hand "soft gripper". For Hand 4, we bought an anatomical skeleton model, sprayed it with silver, and wrapped a metal thread around the fingers to give it a metallic appearance and feel. We could not source a metal gripper for Hand 5. Instead, we used the TinkerKit Braccio Robot gripper [56] that we had in the lab. While the TinkerKit hand does not closely resemble the PR2's design, it has the appearance of a two-fingered gripper with hard materials and metal screws. We call this hand "hard gripper". We replicated Hand 6 using a fabrication model from InMoov, an open-source 3D-printed robot [8]. We called this prototype the "black plastic" hand in the results. For all the hands, we 3D printed a wrist to allow attachment to external hardware.

4.2 Online Evaluation of the Hand Images

We evaluated the seven prototypes using Amazon Mechanical Turk. The procedure was the same as in Study I. For each hand, we prepared an image showing the hand from two angles and scaled them relative to the mug image. We also added the PR2 hand and used the same attention tests as in Study I.

Twenty-two workers responded to the survey. We removed two responses that did not pass the attention tests. The participants (13 female, 7 male) were between 22 and 61 years old. They were from the United States (12), India (4), Brazil (1), France (1), Italy (1), and the United Kingdom (1). In terms of prior experience with robots, 1 self-identified as none, 7 as novice, 7 as beginner, 4 as intermediate, and 1 as expert. The mean of the NARS scores was 12.4 (std = 5.89) on a scale of 6–30, suggesting that, overall, the participants had positive to neutral attitudes toward interacting with robots.

4.3 In-Lab Evaluation of the Hands

We ran a lab-based experiment to collect user ratings of the physical hands after the users saw the hands and were touched by them (Figure 8). We call these conditions *in-lab visual* and *in-lab touch* in the rest of this article.

Study Design. We had two main considerations in our study design. First, we included the seven hands as well as the in-lab visual and touch conditions as within-subjects factors. The main reason for this decision was to allow us to detect any effect, if it exists, despite the variations in subjective ratings (the standard deviation of ratings in Study I was 22.85 on a 0–100 scale). Second, we randomized the presentation order of the seven hands, but the in-person visual condition always preceded the in-person touch condition in our study. We did not counterbalance the order of these two conditions, since the experience of being touched by a robot hand cannot be erased once it is felt. In other words, it was not possible to counterbalance the two conditions in a meaningful way. Furthermore, this order reflects a natural human-robot interaction where, in most cases, a touch interaction happens only after seeing the robot.

To prevent participants from remembering their responses from the in-lab visual evaluation, we asked them to complete a short cognitive task before the touch condition. We used a computerized version of the 2-back task for this purpose. The participant saw a sequence of letters and had to indicate if the current letter matched the one from two steps earlier in the sequence. The 2-back task is a variation of the *n*-back task, which is commonly used for assessing or engaging the working memory [37]. We used the task as a filler to flush the participant's working memory before the in-lab touch condition.

Hardware Setup and Questionnaire. We attached the hands to a UR5e robot arm and programmed a tapping gesture (Figure 8). The wrist connector for each hand could slide in and out of a 3D-printed attachment on the UR5e. The robot arm was controlled via the Robot Operating System (ROS). We programmed the tapping gesture as four up/down movements with 1.5 newtons of force and speed of 16 cm/s. This gesture was designed based on a recent study showing that robot-initiated tapping with these movement parameters can induce emotion associations in users [57]. We adopted these gesture parameters to study if variations in the robot hand can impact the user perception and emotion association.

The questionnaire was similar to that used in Study I with a few changes (Table 1). For evaluation of the physical hands, we removed the robot hand images. Also, we added three open-ended questions at the end to ask about factors that contributed to (1) the participant's ratings of the hand, (2) their emotion ratings, and (3) any change in their ratings before and after the touch.

Procedure. The experiment was advertised through mailing lists, social media posts, and flyers over the University of Copenhagen's campus. The experimental protocol was approved by the ethics board of the university. Each session took between 45 and 90 minutes, and the participants received gifts equal to $23 USD as compensation. At the start, the participants filled out the demographic questionnaire and received a short training on the 2-back task. Then, the experimenter moved the robot to a fixed position for calibration purposes. She then measured the participant's left forearm, marked the 1/3 distance from the participant's elbow, and instructed the participant to align this mark with preset marks on the table. The experimenter also elevated the participant's forearm until it reached a preset height.

Next, the participants evaluated the hands one at a time. For each hand, the participants filled out the questionnaire after seeing the hand (in-lab visual condition). We encouraged the participants to look at the hand from different angles, but they could not touch the hand. Then, the participants completed one round of the 2-back task, the robot hand tapped their left forearm, and the participants evaluated the hand again (in-lab touch condition). At the end of the session, the participants answered the three open-ended questions.

Participants. We recruited 20 new participants (12 female, 7 male, and 1 nonbinary) between 22 and 60 years old. They were from northern Europe (14), Germany (2), Hungary (1), Spain (1), Russia (1), and Argentina (1). For prior experience with robots, 7 self-identified as none, 4 as novice, 5 as beginner, 4 as intermediate, and 0 as expert. The mean of the NARS scores was 12.3 (std = 4.53), suggesting that the participants had positive to neutral attitudes toward interacting with robots.

4.4 Analysis

To analyze the results, we calculated the hand scores along the three dimensions of *Comfortableness*, *Interestingness*, and *Industrialness* derived from Study I. We chose to compute these scores for two reasons. First, running ANOVAs on the 17 rating scales would increase the chance of type I error and using family-wise error correction methods would result in a very small alpha value. Second, individual items on a multi-item questionnaire often have noise. An established practice for dealing with multi-item questionnaires in the literature is to run statistical analysis on the derived components from dimensionality reduction as the derived dimensions are more robust to noise than the individual items [20, 49].

Following the procedure in prior work [20, 49], we computed the three derived ratings by averaging the ratings across high-loading items for each of the PCA components (Table 2). This measure is simple to calculate and interpret. Furthermore, the scores computed with this method for the 73 robot hands in Study I showed strong correlations with the PCA scores (*Comfortableness*, $r(72) = .94$, $p < .0001$; *Interestingness*, $r(72) = .83$, $p < .0001$; *Industrialness*, $r(72) = .82$, $p < .0001$). Thus, similar to prior work, we used this average score as an efficient measure for computing the hand scores along the three dimensions in the rest of our analysis.

4.5 Results

Below, we compare the ratings in the online and in-lab settings and for the in-lab visual and touch conditions using $\alpha = 0.05$ as the significance level. We also summarize comments from the participants.

RQ2. Do user ratings of the hands differ when collected online vs. an in-lab setting?
We ran three separate ANOVAs on the derived ratings for the *Comfortableness*, *Interestingness*, and *Industrialness* as dependent variables and the seven hands (within-subjects) and the online and in-lab visual settings (between-subjects) as independent variables. Since the participants were different in the online and in-lab settings, we regarded the experimental setting as a between-subject factor. All three ANOVAs showed significant main effects of the robot hand ($p < .000$). Since we had selected and designed the hand prototypes to vary in their design features (e.g., number of fingers) and user ratings, we do not further discuss these significant effects.

The ANOVAs did not show a significant effect of the experimental setting or any interaction effect. Thus, we conjecture that the derived ratings were not significantly different between the online vs. in-lab settings in our study (Figure 9). The effect sizes for the online vs. in-lab settings were small (partial $\eta^2 \leq 0.01$) for all three derived ratings, suggesting limited-to-no practical significance of the experimental setting on user evaluation of the hands in our study.

RQ3. Do user ratings change after being touched by the hands?
We ran two-way repeated-measure ANOVAs on the ratings derived for *Comfortableness*, *Interestingness*, and *Industrialness* as dependent variables and the rating condition (in-lab visual vs. touch) and the robot hands (7 levels) as within-subjects factors. The three ANOVAs showed significant main effects of the robot hand ($p < .000$). Similar to RQ2, we do not further discuss these effects.

User ratings did not show a significant effect of the rating condition (i.e., in-lab visual vs. touch) in our study. The effect sizes for the rating condition were small (partial $\eta^2 \leq 0.01$) for all the three derived ratings, suggesting limited-to-no practical significance of touch on the user ratings.

Qualitative Comments. The participants also answered three questions about factors that contributed to (1) their ratings of the hand, (2) emotion ratings, and (3) any change in their ratings before and after the touch. The participant responses to questions 1 and 2 referred to the visual appearance, haptic feel, and materials and texture of the hands as well as their perceived capability. The majority of the participants noted that the visual appearance affected their judgment

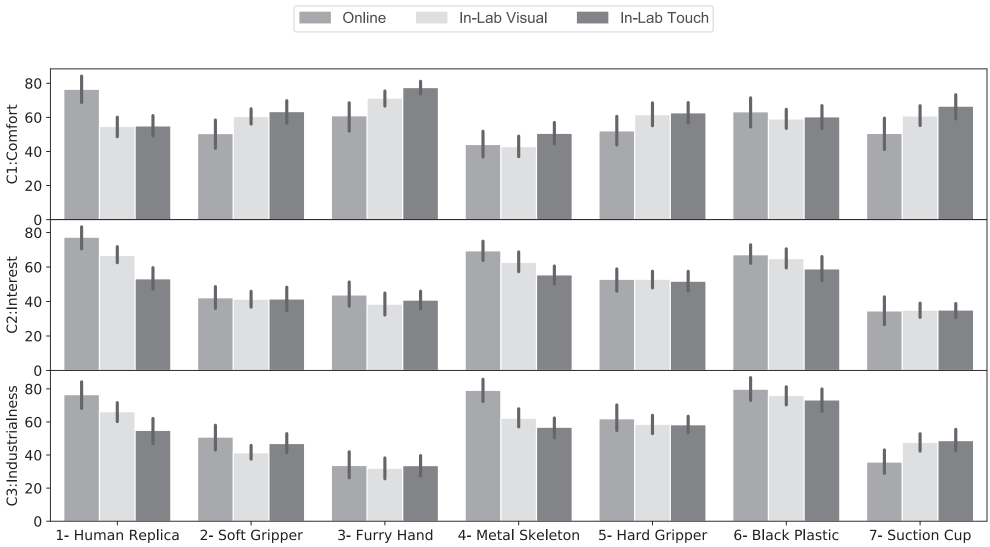


Fig. 9. User ratings for the three derived ratings of *Comfortableness*, *Interestingness*, and *Industrialness* in Study II for the online, in-lab visual, and in-lab touch conditions. The *Comfortableness*, *Interestingness*, and *Industrialness* ratings are calculated by averaging the ratings across high-loading items for each of the PCA components in Table 2 [20].

of the robot hands (n = 15 and 17 participants for questions 1 and 2). Here, the participants mentioned color, size, human likeness, visibility of the mechanical parts, or associations with movies or other familiar objects. About half of the participants mentioned softness, hardness, pressure, or temperature (n = 10 and 11). Several participants indicated that the material and texture of the hands impacted their ratings (n = 7 and 3). Finally, some stated that the perceived capability of the robot hands influenced their judgment (n = 6 and 5).

In contrast to the quantitative results, 15 (out of 20) participants stated that their ratings changed for some or all the robot hands after the touch. *"I noticed I often started seeing them masculine until they tapped my arm, then most felt more feminine." (P11 [female]).* Four participants did not think their ratings changed before and after touch, and one participant did not provide an answer.

5 ROBOTHANDS: AN ONLINE DATABASE AND PREDICTIVE MODELS FOR ROBOT HANDS

To inform the design of robotic hands for social robots, we aimed to build predictive models that could estimate user impressions for a new hand from its design features. Thus, we first identified a set of design features for the hands (e.g., number of fingers), then coded all the hands with their design features and user ratings in a database. We used this database to build a set of regression models that predict user ratings for the hands. Finally, we built an online interface for the database and the predictive models in order to facilitate designers' access and use of our results.

5.1 Coding Design Features of the Hands and Creating a Database

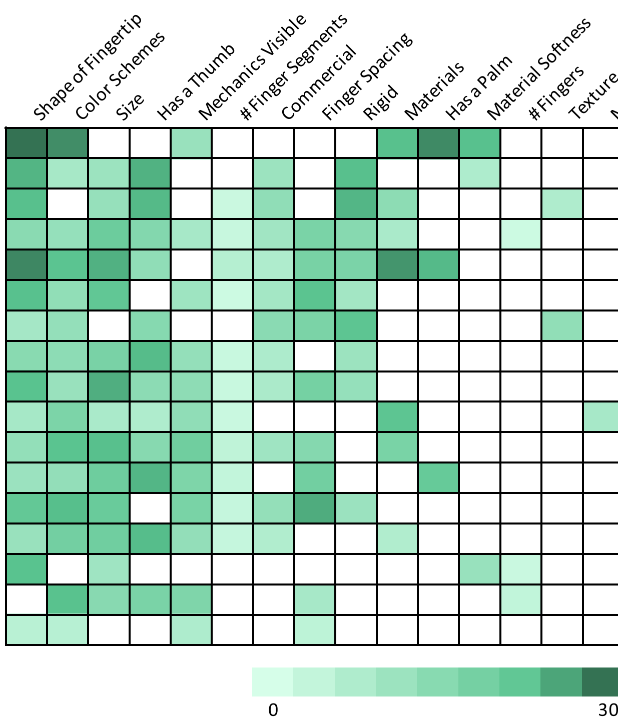
We identified 15 design features for the hands that could help predict user ratings and coded the features for all the hands. Three authors initially agreed on a coding scheme for the hands. Two authors individually coded a random 20% subset of the hands (n = 16). The two authors then met and discussed the disagreements, clarified the definitions, and merged or divided the features.

Table 3. Design features of the robot hands, their range of values, and definitions in our dataset

Hand Feature	Value	Note
Shape of Fingertip	Pointy, Round, Square, Other, N/A	N/A if there are no fingers in the hand.
Color Schemes	Cool, Warm, Mixed (cool + warm), Black, White, Gray, Brown	List of all noticeable color schemes in the hand.
Size	Baby, Kid, Adult, Large	Sizes scaled w.r.t a medium-sized mug: 0 < baby < 0.75, 0.75 ≤ kid < 1.5, 1.5 ≤ adult < 2.25, and large ≥ 2.25+.
Mechanics Visible	Yes, No	Yes, if wires, motors, tendons, pipes, etc., are visible.
Has a Thumb	Yes, No	Thumb should be apart from the other fingers and opposable to them.
Number of Segments in a Finger	0, 1, 2, ...	The maximum number of segments in a finger. A finger has 2+ segments if it has a movable joint. All fingers have at least one segment.
Commercial Product	Yes, No	Yes, if the hand is a commercial product.
Even Finger Spacing	Yes, No, N/A	Yes, if the spacing is even between fingers. N/A if the hand has less than three fingers. Human hand has uneven finger spacing.
Rigid	Yes, No	Yes, if parts of the hand cannot move.
Material	Metal, Plastic, Rubber, Other	List of all visible materials in the hand.
Has a Palm	Yes, No	Palm is the area between fingers and the wrist. To have a palm, the hand must have at least one finger, and the finger(s) must be attached parallel to the palm.
Material Softness	Soft, Hard, Mixed (soft and hard)	Mixed if both types of materials are visible.
Number of Fingers	0, 1, 2, 3, 4, 5, ...	Fingers are the terminal members of the hand that resemble or function like a human finger (e.g., grasping)
Texture	Yes, No	Yes, if individual segments of the hand have a visible texture.
Multicolor	Yes, No	Yes, if there are multiple colors in the hand.

Next, the same two authors coded another 15% of the hands ($n = 11$). The inter-coder agreement score was 92%. One of the authors coded the rest of the hands. These authors did not have access to the ratings collected during the online study prior to coding the hands. This process led to 15 design features for each hand (Table 3). Our focus was on features that can be discerned by a layperson rather than the technical specifications of the hands. Thus, 11 features refer to the visual appearance of the hand, two describe the materials, and one refers to its grasping functionality. We also included whether the hand is a commercial product or not (e.g., research prototype).

Next, we built a database of the 73 hands, their design features, and user ratings. For each hand, we included a name and a link to a reference publication or website. Furthermore, we included the 15 design features for each hand as well as the average user ratings on the 17 semantic differential scales. This database provided the basis for training the predictive models.



	R^2	RMSE	F-Statistic
Humanlike	0.85	9.61	F(10,62) = 33.69
Intelligent	0.81	6.76	F(8,64) = 33.44
Capable	0.81	7.96	F(9,63) = 29.13
Nearby	0.74	5.89	F(11,61) = 15.87
Mature	0.72	9.24	F(15,57) = 9.83
Handover	0.72	6.36	F(9,63) = 17.77
Interesting	0.68	7.57	F(7,65) = 19.68
Trustworthy	0.60	7.07	F(8,64) = 12.19
To Touch	0.59	7.09	F(10,62) = 8.83
Feminine	0.59	7.27	F(10,62) = 8.82
Friendly	0.58	8.38	F(10,62) = 8.65
Be touched	0.57	7.30	F(8,64) = 10.79
Nice	0.57	9.40	F(10,62) = 8.19
Happy	0.55	7.20	F(9,63) = 8.38
Excited	0.48	5.63	F(5,67) = 12.40
Safe	0.47	7.82	F(7,65) = 8.26
Dominant	0.21	4.74	F(4,68) = 4.47

Fig. 10. Contributions of the design features (columns) to the 17 regression models (rows) and the R^2, root mean square error (RMSE), and F-statistic for each model. All the regression models are statistically significant ($p < 0.002$). Higher saturation denotes a higher feature weight (0–30). Feature weights are the sum of the absolute values of the feature coefficients in the regression models (e.g., The absolute values of the coefficients for Baby, Kid, Adult, and Large are summed to present the contribution of the Size feature to the models). The rows and columns are ordered from high to low values of R^2 and feature contributions, respectively.

5.2 Constructing Predictive Models

We developed 17 multiple linear regression models (one for each rating scale) to predict the user ratings for the 73 hands from their design features. First, we converted the categorical features into binary representations using a one-hot-encoding scheme. Next, we identified the top design features for each rating scale by applying forward and backward stepwise regression on the 1,460 (20 users × 73 hands) ratings in our dataset. The results of this feature selection step provided the design features that could help predict each of the user ratings. Finally, we trained a regression model for each of the 17 user ratings.

Figure 10 presents the R^2 values, root mean squared error (RMSE), and selected design features for predicting the user ratings on each of the rating scales. Over 81% of the variance among participants' impressions on Humanlike, Intelligent, and Capable ratings is explained by the design features of the hands ($R^2 \geq 0.81$). Also, over 68% of the variance in the Humanlike, Intelligent, and Capable ratings is accounted for by the design features ($R^2 \geq 0.68$). For seven other rating scales, over 50% of the variance in the user ratings is explained by the design features of the hands ($R^2 > 0.5$). Finally, less than 50% of the variance in the Excited, Safe, and Dominant ratings can be explained by the design features ($R^2 < 0.5$). For all the hands, the RMSE over the 17 ratings is below 10 on a 0–100 rating scale. This error is smaller than the standard deviation of the user ratings for each hand in the online study ($std = 22.85$).

5.3 Analyzing Important Hand Features

Our last research question asks what design features can predict user ratings of the hands (RQ4). We structure this section around the design features (instead of the user ratings), so that designers can check the effect of a single design feature on the user ratings. We order the design features based on how many user ratings each feature helps predict. For each design feature, we denote this number after the feature name.

Shape of Fingertip (16 Models). The shape of finger/gripper tip helps predict the hand score for 16 (out of 17) rating scales. A round or pointy tip for the fingers is positively associated with the Humanlike, Capable, and Intelligent ratings. A round fingertip also increases user comfort to Handover objects. Hands with a square fingertip have lower scores on the Interesting, Feminine, and Mature scales, and the users tend to feel less Excited and more Dominant if touched by these hands. Other fingertip shapes have lower values for Humanlike, Nice, Mature, Friendly, and Trustworthy ratings. Also, the users feel less Happy or comfortable to Be Touched, do Handover, or be Nearby them. When the shape of fingertip is not applicable (i.e., the hand does not have any fingers, such as a suction cup), the user ratings for Mature, Excited, and Comfortable To Touch the hand decrease. Only the predictions for the Safe scale did not depend on the fingertip shape.

Color Scheme (15 Models). The range of skin tone colors, coded as brown in our database, are positively linked to the Humanlike, Nice, Interesting, and Safe ratings. A mix of cool and warm colors lower the Humanlike and Mature scores and increase the Friendly, Happy, and Dominant ratings. Black and gray colors lower the Feminine rating, warm colors (but not skin tone) decrease the Safe rating, while cool colors increase the Intelligent score. Interestingly, the white color has a negative impact on the perception of how Nice, Friendly, and Trustworthy the hand is and how Happy and comfortable people feel to have physical interactions (To Touch, Be Touched, Handover, Nearby) with it.

Size (14 Models). The adult hand size increases the Capable, Mature, and Intelligent scores, and it lowers the Feminine and Comfortable To Touch scores. Hands with the kid size are perceived as less Mature, and the users feel less Excited after being touched by these hands. The baby hand size is perceived less Nice, Safe, Friendly, and Trustworthy than the hands with other sizes, and people feel less Happy and comfortable to have physical interactions with it. The baby hand sizes in our database either had a rigid design or were among the soft manipulators with nuanced working mechanisms. Both designs were negatively evaluated by the users.

Mechanics Visible (12 Models). Visible wires and motors make the hand less Humanlike, Nice, Safe, Feminine, Friendly, and Trustworthy. Also, the users feel less Happy, Dominant, and Comfortable to have physical interactions with the hand compared to when no mechanics are visible.

Has a Thumb (12 Models). Hands with a thumb are perceived as more Interesting, Capable, Safe, Feminine, Mature, Friendly, Intelligent, and Trustworthy than those without a thumb. Also, having a thumb improves how Happy and Comfortable the users are To Touch, Be Touched, or Be Nearby the hand.

Number of Finger Segments (11 Models). Hands with more finger segments are rated as more Capable and Mature but also less Nice, Feminine, Friendly, and Trustworthy. The users are less Happy and less Comfortable to have physical interactions with the hand (To Touch, Be Touched, Handover, Nearby) compared to the hands with fewer segments.

Commercial Product (11 Models). In our models, the commercial hands scored higher than the research prototypes on the Nice, Interesting, Capable, Mature, Friendly, Intelligent, Trustworthy, Happy, Comfortable To Touch, Handover, and Nearby user ratings.

Finger Spacing (10 Models). Uneven spacing of fingers (e.g., human hand) is positively linked to the Nice, Mature, and Friendly ratings. The uneven spacing also increases scores on feeling Dominant and Comfortable to have physical interactions with the robotic hand. Even finger spacing (e.g., in grippers) lowers the Nice rating. When this feature is not applicable (i.e., the hand does not have any fingers), the hand is perceived as less Interesting and Safe to users.

Rigid (9 Models). Hands that cannot close or move their fingers score low on Nice, Interesting, Capable, Mature, Intelligent, and Trustworthy ratings. The Comfort To Touch, Handover, or Nearby ratings are lower for these hands, too.

Materials (7 Models). Hands with metal components get higher scores on Capable and Mature rating scales and lower scores on the Humanlike, Feminine, Friendly, and Happy ratings compared to hands with other materials. Rubber hands get high scores on Humanlike and Mature, while plastic hands get lower Mature ratings. Hands with other materials get lower scores on the Feminine and Comfortable to be Nearby ratings.

Has a Palm (3 Models), Material Softness (3 Models), and Number of Fingers (3 Models). Having a palm has a high weight on the Humanlike score (i.e., its coefficient is 24.5 out of 30). However, having a palm lowers the Mature and Comfortable to Be Touched by the Hand ratings. Soft materials increase the Humanlike score, while hard materials increase the Intelligent and Excited ratings. Hands with more fingers get higher scores on the Excited rating and a lower score on the Safe and Comfortable to be Nearby ratings. Surprisingly, the other models do not rely on the number of fingers in their predictions.

Visible Texture (2 Models) and Multicolor (1 Model). Hands without a visible surface texture get lower values on the Interesting and Capable ratings compared to those with a visible texture. Hands without a Multicolor feature get lower Feminine ratings compared to the hands with this feature.

5.4 Introducing the RobotHands Interface

We created an online visualization, available at https://robothands.org, to facilitate access to the RobotHands dataset and predictive models. The code for the interface is adapted from the open-source code by the Locomotion Vault project [24].

The RobotHands interface provides five main functionalities: (1) The *Home* page provides a summary of the project together with links for downloading the dataset of 73 hands and the larger set of 378 hands; (2) On the *Gallery* tab, users can browse the 73 hands with their images and full database record; (3) The *Similarity* tab presents the hands along the three PCA dimensions. This view allows users to see trends in user ratings of the hands and find similar hands based on overall user ratings; (4) With the *Filters*, one can search the database for a subset of design features or user ratings; (5) On the *Prediction* tab, designers can get a quantitative estimate of user ratings for a new hand by entering its design features.

6 DISCUSSION

Below, we discuss findings from the two studies in light of prior work and provide guidelines for designing or customizing robot hands for positive user ratings. We reflect on the limitations of the work and suggest avenues for future research.

6.1 Reflections on Study Results

Results of our online study suggest that *Comfortableness*, *Interestingness*, and *Industrialness* of the hands capture variations in the user ratings of existing robot hands. These results are most related to a recent study by Carpinella et al. on user perception of social robots [20]. Specifically, Carpinella et al. found that three factors of competence, warmth, and comfort can describe user evaluation of robots [20]. The *Comfortableness* dimension in our results (D1) is in line with the comfort factor reported by Carpinella et al. The *Interestingness* dimension (D2) is linked to the ratings of Interesting, Intelligent, Capable, Humanlike, and Mature for the hands. We conjecture that this dimension is related to the competence factor in the previous work. Our analysis does not show the warmth factor that was reported by Carpinella et al. The *Industrialness* dimension (D3) in our study is negatively linked to the Feminine ratings and is positively related to the ratings of Maturity and Capability. While we are not aware of previous studies that show this factor for robots, the negative link between Feminine ratings and the Mature and Capable ratings may reflect some of the reported prejudice in evaluating people based on their gender in male-dominated areas [25].

Results from the in-lab study suggest that the visual evaluation of robot hands may be robust to physical presence and touch interaction. With 40 participants, we did not find any significant difference between user ratings in the online setting and the in-lab visual condition (RQ2). Similarly, we did not find a significant difference between the in-lab visual and in-lab touch conditions with 20 participants (RQ3). These sample sizes are consistent with previous studies in haptics and HRI [30, 52, 54, 59], but we cannot completely rule out the impact of physical presence and touch on user ratings. In other words, a larger study may have found a statistically significant difference. Thus, our results must be considered as a first exploratory study on these aspects rather than a definitive answer. On the other hand, the effect sizes for the experimental setting and rating conditions in our study are small for all the statistical tests, suggesting that the practical significance of these factors, even if the results were statistically significant, may be small. One interpretation for the lack of statistical difference in the ratings could be that the user judgment of the hands did not change in the same way across the participants after the touch. In other words, the participants differed in their expectations of how the hands would feel in the vision condition. Thus, while the ratings have changed for individual participants after touch, the change in perception was not robust across all the participants. Our results are in line with haptics and HRI research that shows people can infer tactile sensations and their affective associations through vision [12, 35, 52, 59, 60]. On the other hand, our results are in contrast with studies that show the importance of social touch in HRI and statistically significant change in user perception or behavior across all the participants. The work of Shiomi et al. is relevant in particular [54]. Shiomi et al. ran a between-subject study with three conditions: (1) observe a robot, (2) touch a robot, and (3) touch a robot and the robot touches back. With 11 participants in each condition, Shiomi et al. found that the participants rated the robot as friendlier when the robot touched them back. The contrasting results between their work and ours could be due to the touch interaction, perceived autonomy of the robot, or cultural aspects of touch. Shiomi et al. used a stroking gesture, which is commonly associated with an affective intent. Also, Shiomi et al. used a humanoid robot that spoke with the participants and appeared fully autonomous. Finally, Shiomi et al.'s study was conducted in Japan. We conjecture that the perceived intent and autonomy of the robot and cultural factors may mediate the effect of touch on user evaluation of robots.

6.2 Implications for Robot Hand Design

The design features selected for the regression models provide guidelines for predicting user ratings of robot hands. Specifically, feature values similar to the human hand create positive impressions (i.e., higher values on the rating scales). For example, the round fingertip, brown color, adult hand size, having a thumb, and uneven finger spacing increase the scores for the majority ($\geq$11) of the user ratings. A notable exception is the number of fingers, which does not have much influence on user ratings. Thus, designers can use fewer or more fingers based on the technical considerations of the target domain. Also, having a palm increases the score for Humanlike and reduces Mature and Comfort to Be Touched ratings, but it has little effect on the other ratings. More finger segments are also associated with higher Capable and Mature ratings, and adding visible surface texture improves Interesting and Capable ratings. On the other hand, some features create negative impressions (i.e., lower user ratings) and should be avoided. For example, the white color is frequently used in designing social robots, but our data suggest it is perceived negatively by users. Fingertips that are not round or pointy can also create negative impressions.

Some of the hand features, such as color scheme and surface texture, can be easily modified by designers. Others, including the shape of fingertips, size, surface materials, and visibility of the hand mechanics, can be optimized for both user experience and functionality if these features are considered at the design stage. For example, a round fingertip is linked to positive user impressions and can also have good dexterity and sensing [26]. Finally, design features such as if the hand is rigid, if it has a palm, or the number of segments in each finger can fundamentally change the technical specifications. Thus, these features pose a tradeoff for design.

The RobotHands dataset can further facilitate the selection and design of robot hands. At the most basic level, one can explore the variety of existing designs in the database before choosing or building a hand. When using an existing robot, HRI designers and researchers can look up the user ratings of its end effector or a similar design in the database. With this knowledge, the designers can decide to customize the hand or account for the user perception ratings in their studies. Designers can check the overall trends in user ratings in the Similarity tab or use the predictive models to obtain a quantitative estimate for a new design.

6.3 Limitations and Future Work

Our work has a few main limitations that can be examined in future studies. First, we did not investigate the effect of grasping and motion parameters on user perceptions of the hands. This was a pragmatic choice. The existing videos of the 73 robot hands in Study I had different viewpoints and demonstrated different object interactions. These differences could unfairly bias user evaluation. Thus, we decided to use images and edit them for consistency in the presentation. In Study II, we controlled all the motion parameters to only investigate the impact of the hand. A future direction would be to systematically study the impact of hand motion parameters and object interactions on user ratings of the hands. Second, the curated robot hand images in our database had some variations (e.g., different presentation angles for the hands). While we attempted to make the images consistent by removing their backgrounds and objects, we could not find existing images that showed all the hands in the same angles and poses. Our database was not large enough to analyze the effect of these variations on the user impressions of the hands. Future work can systematically vary the presentation of a subset of the hands and assess their impact on user ratings for the hands. Third, the 17 rating scales in our studies may have limited participant responses to predefined qualities. We opted for a structured questionnaire to be able to chart user impressions of a large variety of robot hands. A complementary approach would be to conduct open-ended interviews with a smaller subset of representative hands. Such studies have been used to shed light on nuances of user experience with other technological artifacts [41]. Also, using a custom questionnaire makes it hard to compare our results with previous studies of robots. While we could not find an appropriate validated questionnaire for our work, our results can inform the development of a validated instrument for robot hands in the future. Fourth, our results mostly reflect the perception of American and European users (>75% of the participants) who opted to participate in our study. Future studies can investigate whether the same trends hold for other cultures and for those with a negative attitude toward robots. Finally, our design features and predictive models need to be validated with a larger number of robot hands. In our work, we used two coders for assigning the hand features and developed regression models with a feature selection scheme to mitigate the possibility of overfitting to the current dataset. Thus, the models and design features that we presented in this article need to be tested and validated on a larger set of robot hands in the future.

Another interesting avenue for future work is user perception of prosthetic hands. Our initial observations suggest that existing prosthetic hand designs are a subset of the robot hands in our database but with more variation in colors and graphical patterns. For example, prosthetic users may have passive limbs, grippers, five-fingered designs, or activity-specific tools as a hand. In our studies, we explicitly asked users to imagine that the hands in our database belong to a robot rather than a human. Future work can investigate how an observer's perception of the hand and touch interactions can change when a robotic hand is embodied or controlled by a human rather than a robot.

7 CONCLUSION

We chart user impressions of existing robot hands in two user studies. Our results suggest that people may form robust visual impressions of the hands that do not easily change with touch. These rated impressions can be estimated based on the visual and haptic features of the hands. We provide practical design guidelines that can improve the user experience of robots without significantly changing their technical complexity. We present our data and predictive models in the RobotHands online interface to facilitate the selection and design of future robot hands by researchers and practitioners.

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