What Should Robots Feel Like? Factors that Influence the Perception of Robot-Skin

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ABSTRACT

It's widely accepted that a robot's embodiment plays an important role during human-robot interaction (HRI). While many studies have explored the effect of robot appearance, relatively little is known about how the texture and stiffness of the surface material, or what may be referred to as 'robot-skin', influences how the robot is perceived. Gaining improved understanding in this area may have direct and actionable consequences on robot design, since at present nearly all commercially available service robots have similar exterior surfaces composed of smooth, stiff materials, usually plastic. This study is framed around systematically investigating the type of textures that may be better suited for these robots. First, experiments were undertaken to classify the textural characteristics of 27 distinct materials which could potentially be used as a robot-skin. A representative subset of these materials was then selected for a second experiment that explored how the stiffness and tactile properties of the material influenced its perceived suitability for use on a service robot. The research found that people strongly preferred surface textures that were soft, rather than stiff. The most suitable material stiffness was found to be context dependent; soft options were preferred in the blind test condition, but for cases where participants were presented with the 3D image of a service robot in an immersive virtual reality environment, medium stiffness materials were preferred. In the final part of the study, we identified a range of textural properties that seem to correlate with high and low suitability for use on service robots. It is hoped that these findings are useful to help inform the design of future HRI systems, and motivate further investigation into the social roles of robot-skin.

CCS CONCEPTS

• **Computer systems organization → External interfaces for robotics**; • **Human-centered computing → User studies**; *Virtual reality*; **Empirical studies in HCI**; **Systems and tools for interaction design**.

KEYWORDS

human-robot interaction; robot skin; texture analysis; haptics; virtual reality; mixed-methods

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1 INTRODUCTION

For humans and other animals, the skin is a large and complex organ which acts as the interface between internal organs and the external world [6, 10]. It has a large number of physical functions, which can be classified as boundary functions (mechanical protection, chemical control/protection, UV radiation protection, barrier to pathogens and microbes, temperature regulation, repair) and sensing functions (temperature, pressure, texture, vibrations, pain). The skin can also have important uses in a social context. In primates, time spent engaged in social grooming significantly surpasses time spent self-grooming, and evidence suggests that it is key to building friendships, reducing stress and gaining improved psychological health [8]. Skin can communicate general information pertaining to overall health, age, gender, etc. It can also help communicate affective states, both visually and haptically through interpersonal touch [9, 12].

Given its utility and necessity in the natural world, service robots require outer surfaces that approximate (at least some) of the functions of human skin [18]. To date, relatively few studies have examined how skin texture, defined by the Merriam-Webster dictionary as the "visual or tactile surface characteristics and appearance of something", influences perceptions of robots in tasks involving human-robot interaction (HRI). In this study, we first classified 27 different materials, each with properties that could be utilized as a skin-like exterior for a robot. Taking a representative sample of these materials, we then explored their perceived suitability for use on a service robot platform. We decided to focus the application of the study on service robots due to their growing ubiquity, their common requirement for interaction with people, and since it was observed that at present, nearly all off-the-shelf service robots possess the same hard-plastic outer surfaces.

2 PRIOR WORK

Much of the existing body of literature that has investigated the surface material of a robot’s embodiment (referred to in this study as *robot-skin*) has focused on replicating physical functions, most commonly tactile sensing [11, 21, 30]. Relatively little research has focused on the social aspects of skin, and on understanding how the appearance and texture of *robot-skin* can influence HRI.

Research by Bartneck et al. has indicated that the color of a robot can have a priming effect, and invoke (at least with some people) a perception that a robot possesses a race identity [3]. The color of *robot-skin* has also been shown to be effective in the communication of synthetic emotional states [27].

Researchers exploring the social function of *robot-skin* have shown it plays an important role in active [20], communicative [33] and affective touch [2, 34]. While many researchers have explored touch in HRI, it is observed that few have focused on understanding how the texture of *robot-skin* influences HRI [25]. While rarely studied directly, it would seem that skin texture is an important design consideration in the creation of therapeutic robots that provide emotional support through affective touch; many of the platforms commonly used, such as Paro [15], Probo [23], Huggable [13], all tend to utilize outer materials that are soft, cushioned and have a texture that is pleasant to the touch. Recently, Hu and Hoffmann explored using dynamic changes in skin texture to communicate changes in the robots affective state [14]. Another recent study indicates that people are more likely to engage in touch-based interaction with a robot if it has a textured skin, rather than a standard hard-plastic shell [16].

A review of the literature indicates that classification methods for texture are context dependent, and vary significantly across applications. For example, notable differences exist between the measurement instruments for visual texture and haptic texture. Some studies on material texture perception focus more on the language used to describe visual texture [32]. In a highly cited study by Bhushan et al. [4], researchers takes a list of texture terms and grouped them into 11 classes using hierarchical clustering. A multi-dimensional analysis was then conducted, and it was found that 3 dimensions accounted for 82% of the variability of the subject data. In [29], the authors present results of a free sorting task of 124 different material samples using multidimensional scaling. It was found that the relevant number of dimensions for haptic perception of materials is estimated to be 4.

3 METHODS

The study is presented in two parts. First, due to limitations in the available material texture classification literature[1], a study was undertaken to classify a range of materials with different textural properties that may be suitable for use as a *robot-skin*. Then, using the findings from the first experiment, a representative sample of the classified textures were selected for a second experiment which explored the perceived suitability of different materials for use as a *robot-skin*.

[1]As outlined in section 2, published studies rarely provide precise detail on the exact materials used, few use a large sample size, and many adopt differing classification scales making them difficult to aggregate.

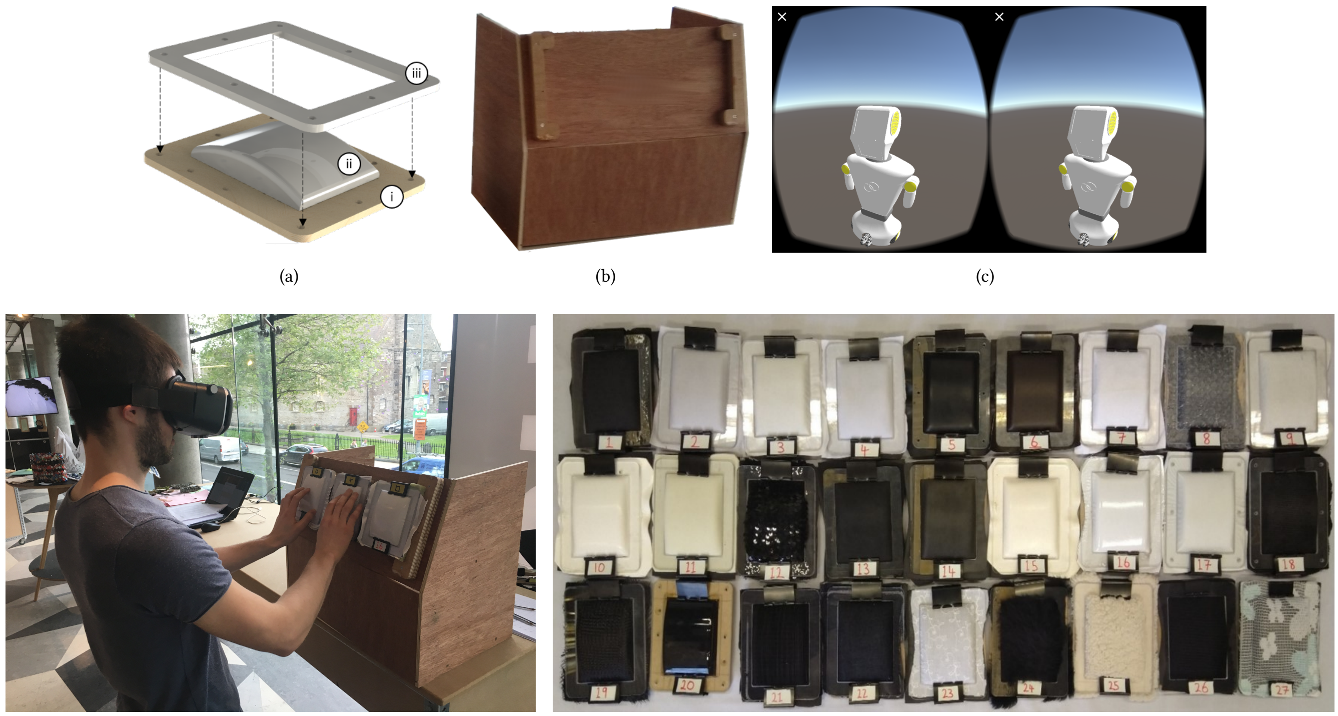
Table 1: Materials used for skin texture classification experiment. The materials with the asterisk (*) were used in the *robot-skin* suitability experiment.

Code	Material Specification	Color
M1	Wetsuit Neoprene	Black
M2	Polyurethane Laminate (PUL) [64% polyester, 36% polyurethane]	White
*M3	100% Polyester Waterproof Canvas [800 denier]	White
M4	Food-safe Polyurethane Laminate (PUL) [75% polyester 25% polyurethane]	White
*M5	Neoprene Rubber [1.5mm]	Black
M6	Imitation Leather	Brown
M7	100% Polyester (plain)	White
M8	Bubble wrap	Transp.
M9	Polyester (fabric used on *Stevie* robot [19])	White
M10	Silicone Rubber [1.5mm]	White
M11	Ethylene Propylene Diene Monomer (EPDM) rubber [3mm]	White
M12	Sequin material	Black
M13	Neoprene rubber [3mm]	Black
*M14	Polyethelene rubber [3mm]	Black
*M15	Nitrile Rubber [1.5mm]	White
*M16	PVC strech fabric	White
*M17	Food Safe Polyester-Vinyl [75% vinyl, 25% polyester]	White
M18	Corduroy	Black
*M19	PolyEthylene Terepthalate (PET) Expandable Braided Sleeving	Black
M20	1mm Acrylic (vacuum formed)	Black
*M21	100% Polyester (Pleated)	Black
M22	Denim Jean	Black
M23	100% Cotton (embroidered texture)	White
M24	Acrylic Fur	Black
*M25	Lambskin Ivory 100% Polyester	White
M26	Rib Jersey (95% Polyester, 5% Elastaine)	Black
M27	100% Polyester (embroidered texture)	White

Undertaking experiments of this nature involving so many materials, a trade-off had to be made in the experimental design between what was most desirable (i.e. using real robots fitted with the materials under consideration) and what was practical (i.e. a test that could be performed systematically, easily repeated, and could be undertaken in a reasonable amount of time). To overcome this constraint, a bespoke piece of testing equipment was specially designed and constructed. Supported by this apparatus, participants were presented with small rectangular samples of the test material, and then prompted with a series of questions, utilizing both qualitative and quantitative forms of data collection.

3.1 Design of Testing Apparatus

The testing apparatus comprised three components: a sample holder, mounting plate, and test rig. The sample holder was a rectangular fixture, designed to ensure uniform tension was maintained across



(a) (b) (c)

(d) (e)

Figure 1: Illustration of the testing procedure. (a) components of sample holder: (i) baseplate that attaches to mounting plate, (ii) mould that test material is draped over, (iii) tension plate used to ensure test material is taut around the mould; (b) Testing rig used to secure the mounting plates that comprised test samples; (c) 3D virtual image of *Stevie* robot presented to participants completing experiment 2 in the ‘robot-visualization’ condition; (d) Photo of participant interacting with test samples during experiment 2; (e) 27 materials tested in experiment 1, mounted in sample holders with material code labels.

a textile material. Sample preparation involved draping the test material over a plastic mould, and then securing it a fastening plate (using clips) to ensure that the material was suitably taut (Fig. 1(a)). When prepared, the surface area of each test sample was approximately 90x110mm. Material samples were then secured to a mounting plate (which could attach 1-3 samples at a time), which in turn could be then fixed to a stationary test rig (Fig. 1(b)). The design of this rig allowed quick changing of samples; this was critical given the number of tests to be conducted during the study. A participant interacting with samples mounted on the apparatus is presented in Figure 1(d).

3.2 Experiment 1: *Robot-skin* Texture Classification

The first experiment involved classifying 27 distinct materials, spanning a wide range of different textures and properties. Samples included technical materials such as foams and rubber compounds, as well as more familiar materials such as acrylic, common textiles and wools. To minimize potential confounding effects, only samples with a neutral color were used. As all samples were prepared in identical sample holders, differences in material stiffness were a property of the material, not the supporting structure. Only one of the 27 samples (M20) was not a textile; rather, this material was a thermoplastic and was chosen due to its similarity with the kind of hard-plastic material commonly used as the external shell on off-the-shelf service robots. This sample was created through a vacuum forming process and had the same size/shape characteristics as the other samples.

During the experiment, participants were presented with samples one at a time, and were then asked how they might describe the material and to comment on aspects that they liked/disliked. Next, they were asked to rate the material on 6 semantic differential scales. These scales reflect the most commonly used across the literature on texture classification and included: Warm-Cool [7, 28, 35], Rough-Smooth [1, 5, 7, 7, 17, 22, 24, 26, 28, 35], Coarse-Fine [1, 5, 22, 24, 26, 31], Complex-Uniform [1, 5, 22, 26] Sticky-Slippery [24, 28], and Soft-Hard [7, 24, 28, 35].

Materials were presented in random order, and each participant rated 9 different materials. Each test lasted approximately 15-20 minutes and the audio from each session was recorded.

3.3 Experiment 2: Evaluation of *Robot-skin* Texture Suitability

The goal of the second experiment was to explore the perceived suitability of different material compositions for use as a *robot-skin*. For each material tested, participants were presented with three samples, each with a different relative stiffness. The material stiffness (3 levels: soft, medium, hard) was controlled through the use of different foam under-layers placed between the sample holder and the test material. The ordering of the independent variables (i.e. material, relative stiffness) was randomized throughout the experiment.

To explore if the stiffness of the surface material influenced how people might perceive a service robot, participants were asked to select the sample with the stiffness that was most appropriate for a service robot. To better understand how the material itself contributed towards this perception, they were then asked to rate the overall suitability of the material (independent of stiffness) on a 7 point scale (1: highly unsuitable, 7: highly suitable). To provide further insights, participants were invited to provide free response verbal feedback on each material, which was then logged by the experimenter.

To help maintain a suspension of disbelief, participants were required to wear a virtual reality (VR) headset (obscuring view of the testing apparatus) and were prompted to *"imagine reaching out and touching a robot with the corresponding material covering"* . This process is illustrated in Figure 1(d). Depending on the test condition, the VR headset either presented a black display ('blind' condition) or a responsive digital 3D image of a service robot ('robot-visualization' condition). The robot presented in the robot-visualization condition was the *Stevie* robot [19]; during these interactions, the robot was stationary and was positioned with a neutral background. A sample view of the robot from the VR headset is given in Figure 1(c). The VR effect was generated using the Unity programming environment and was rendered on an Android phone mounted inside a VR headset. The relatively low resolution of the display resulted in the clarity of the image being too low to perceive a defined surface texture on the virtual robot.

For practical reasons, it was not feasible to evaluate the suitability of all 27 materials classified in experiment 1, as this would have involved preparing 81 distinct samples (27x3) and taken several months to complete tests (given available access to the experimental space). Ultimately, nine materials (9x3 samples) were shortlisted, which maintained continuity with the sample size of the first experiment. To ensure that materials tested were representative of a wide range of textural properties, efforts were made to ensure that materials included in the test-set corresponded to each of 12 adjective pairs (at two materials per adjective label) used in the rating scale in experiment 1. To ensure repeatability of the experiment, only materials where the exact material composition was known, or where a manufacturer serial number was available were considered. The materials used in experiment 2 are identified with asterisks in table 1.

4 RESULTS

4.1 Participants

All experiments took place in a public gallery space in the city centre of a major European city, located adjacent to the host University. Participants did not receive any payment for taking part. Ethical approval for the study was provided by the University Institutional Review Board, and written informed consent was provided by each participant. Background demographic information for experiment 1 (n=39) and experiment 2 (n=60) is given in Table 2; this covers participant gender, age, English proficiency level and nationality. In addition to the standard demographic questions, participants were asked if they had any formal affiliation with the host University that was conducting the study. In the first experiment 59% had no affiliation; in the second experiment, 80% had no affiliation. All experiments began with a short training period. During this time, participants were given a high-level introduction to service robots, referencing among other things the range of tasks they might perform, how they will be required to work alongside people and their general size.

Table 2: Participant Demographics for experiment 1 and 2.

	Age		Gender				English Proficiency		
	Age	Std. Dev	Female	Male	Other	Prefer not say	Native	Fluent	Basic
Exp 1	31.0	13.7	53.8% (21)	43.6% (17)	2.6% (1)	0% (0)	58.9% (23)	35.9% (14)	5.2% (2)
Exp 2	30.2	11.7	45% (27)	51.7% (31)	1.65% (1)	1.65% (1)	76.7% (46)	18.3% (11)	5% (3)

	Nationality																			
	Ireland	Nigeria	UK	USA	Germany	Spain	Brazil	Australia	Russia	India	Holland	Ukraine	Cyprus	Italy	Lithuania	Slovakia	France	Poland	Canada	Unknown
Exp 1	27	1	4	1	3	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Exp 2	27	0	8	9	0	0	0	3	2	1	1	1	1	1	1	1	1	1	1	1

4.2 Experiment 1: *Robot-skin* Texture Classification

Results from the first experiment are presented in two parts; one part pertaining to a quantitative analysis and one to qualitative analysis. First, for each of the materials tested, a weighted score was computed for each of the six texture classification scales. This score provided an estimate of where in the semantic difference scale the material was perceived to fit, and was computed using the following formula:

$$\sum_{n=1}^{5} \alpha_n (n-3)$$

where n is the rating value on the five-point scale and α_n is the frequency that rating value was chosen for the given material. The scores computed for each material, which indicated their relative positions on the texture rating scales, are given in Figures 2(a)-2(f).

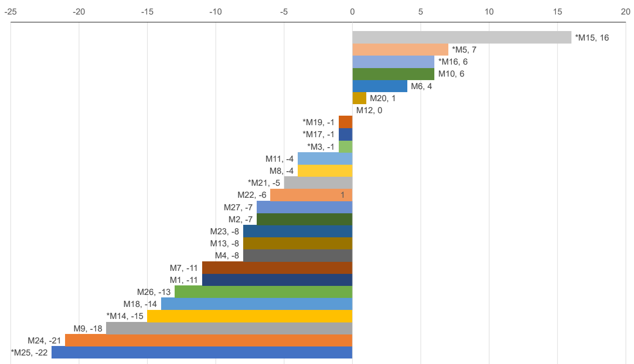
The most common free-form descriptors used to describe each material are given in Table 3. Only descriptors that were used at least twice are listed.

4.3 Experiment 2: Evaluation of *Robot-skin* Texture Suitability

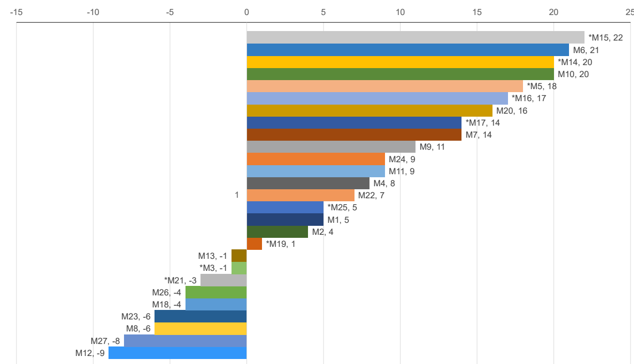
In the second experiment, we set out to investigate several research questions.

RQ_1: **Is there an optimal stiffness for a *robot-skin*?**

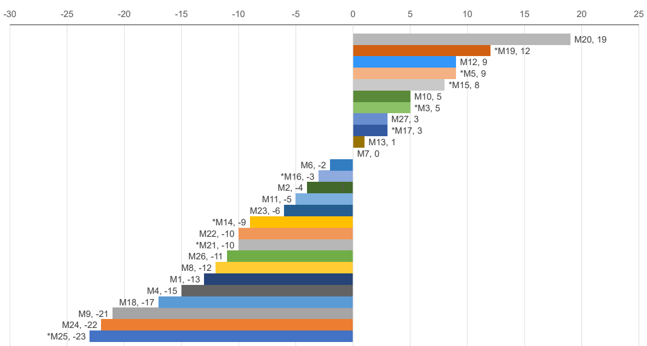
The preferred stiffness for each of the material samples was analyzed (Fig. 3). A Chi square test of independence was conducted



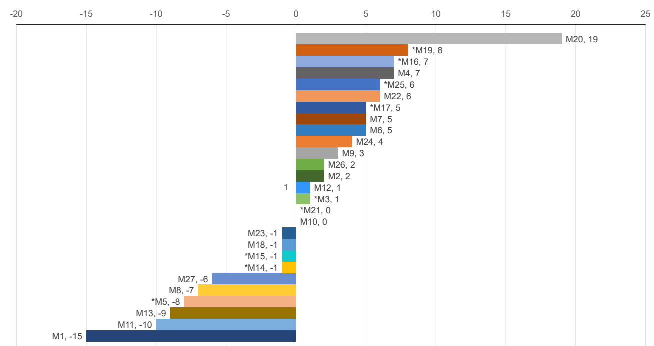
(a) warm-cool



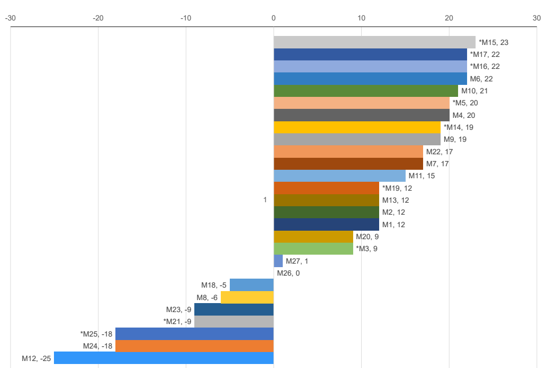
(b) rough-smooth



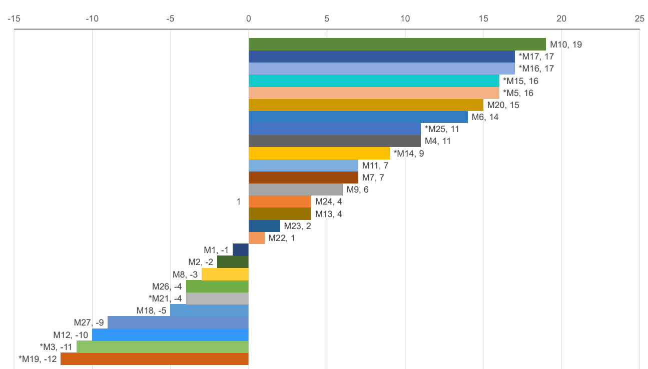
(c) soft-hard



(d) sticky-slippery



(e) complex-uniform



(f) coarse-fine

Figure 2: Texture classification of 27 materials across the six semantic difference scales. The materials with the asterisk (*) were used in the *robot-skin* suitability experiment.

comparing the preferred *robot-skin* stiffness for each exposure condition (blind/robot-visualization). A significant interaction was found between the (soft/medium/hard) stiffness conditions for both blind ($\chi^2(2, N = 60) = 37.2, p < 0.01$) and robot-visualization conditions ($\chi^2(2, N = 60) = 24.2, p < 0.01$).

A Chi Square test of independence revealed that the stiffness preference and exposure condition were significantly associated ($\chi^2(2, N = 60) = 7.5, p < 0.05$). Post hoc comparisons (with Bonferroni correction) of the stiffness settings and exposure conditions revealed a preference in the blind condition for a softer material, and a preference in the robot-visualization condition for a medium stiffness material. In comparison, stiffness preferences were statistically similar between soft and hard settings, and medium and hard settings.

RQ_2:Does robot visualization effect material preference?

A Wilcoxon Signed-ranks test indicated that material M19 was preferred more in the robot-visualization condition (Mdn. = 4.5)

Table 3: Free response descriptors used to describe each of the classified materials. The frequency of response is provided in parenthesis. The materials with the asterisk (*) were used in the *robot-skin* suitability experiment.

Code	Material Specification
M1	sticky (7), soft (5), rubbery (3), warm (2)
M2	rough (4), smooth (4), coarse (3), thin (2), soft (2), directional (2), fabric (2)
*M3	rough (3), coarse (3), uncomfortable (2), grainy (2), directional (2), soft (2)
M4	soft (5), uniform (5), coarse (5), fine (5)
*M5	sticky (5), hard (4), cold (5), smooth (5), rubbery (2), leathery (2)
M6	smooth (4), cool (3), leathery (3), shiny (2), firm (2), uniform (2), sticky (2)
M7	soft (4), ,sticky (2), smooth (2), fine (2)
M8	bumpy (4), sticky (4), soft (3), textured (2), protective (2), warm (2)
M9	soft (8), smooth (3), uniform (3), comforting (2), animal-like (2), coarse (2), warm (2)
M10	smooth (7), slippery (4), sticky (4), plasticy (3), quality (2), rubbery (2), hard (2), tacky (2)
M11	spongy (4), sticky (4), smooth (3), soft (3)
M12	complex (5), directional (4), hard (3), scaley (3), weird (2)
M13	sticky (3), soft (3), rough (2), weird (2), spongy (2), coarse (2), un-inviting (2)
*M14	soft (6), warm (5), smooth (5)
*M15	sticky (6), smooth (5), plasticy (3), cold (3), dirty (2), hard (2)
*M16	smooth (7), plasticy (5), sticky (3), shiny (3)
*M17	smooth (7), slippery (4), sticky (4), plasticity (3), quality (2), rubbery (2), hard (2), tacky (2)
M18	soft (4), rough (3), comforting (3), familiar (3), coarse (2), ribbed (2)
*M19	coarse (3), smooth (3), uniform (3), interesting (3), shiny (2), artificial (2, rough (2)
M20	hard (4), smooth (3), slippery (2)
*M21	soft (5), weird (2), rough (2), complex (2), textured (2)
M22	coarse (5), uniform (4), soft (2), smooth (2), fabric (2), familiar (2)
M23	rough (3), textured (2), fine (2), hard (2), soft (2)
M24	fluffy (6), animal-like (4), soft (4), cozy (2), warm (2)
*M25	soft (8), fluffy (4), warm (4), comforting (4), animal-like (3), cozy (3), furry (2), clumpy (2), smooth (2)
M26	directional (2), rough (2), bumpy (2), soft (2)
M27	rough (5), coarse (3), bumpy (2), patterned (2), uncomfortable (2)

than the blind condition (Mdn. = 3), Z = 110.5, p < .05, r = 0.4. No other preferences were found between exposure conditions at a significant level.

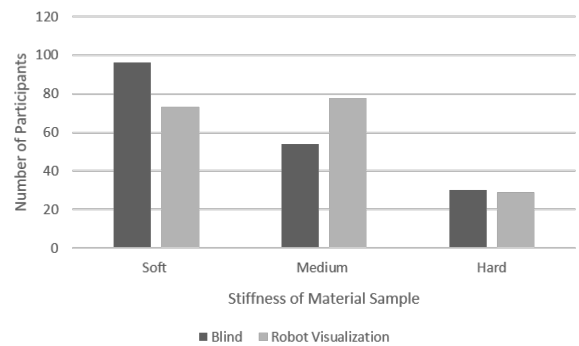


Figure 3: Preferred stiffness for the materials tested in experiment 2.

RQ$_3$: **Is there a favourite texture for a *robot-skin*?** Ratings matching the 9 test materials with perceived suitability for use on a service robot were aggregated for both exposure conditions. These results, undertaken using a 7 point ordinal differential scale, are presented in Figure 4.

A one way ordinal regression analysis indicated that there was a significant effect between the perceived suitability of the materials tested ($\chi^2(8, N = 60) = 41.2, p < 0.01$). Post hoc tests were conducted which involved conducting pairwise Tukey-adjusted comparisons. Significant differences were found between the following materials at the 95% confidence level (the first index indicates the preferred material): M3-M25, M5-M25, M14-M19, M14-M25, M17-M15, M16-M25, M17-M19, M17-M21, M17-M25.

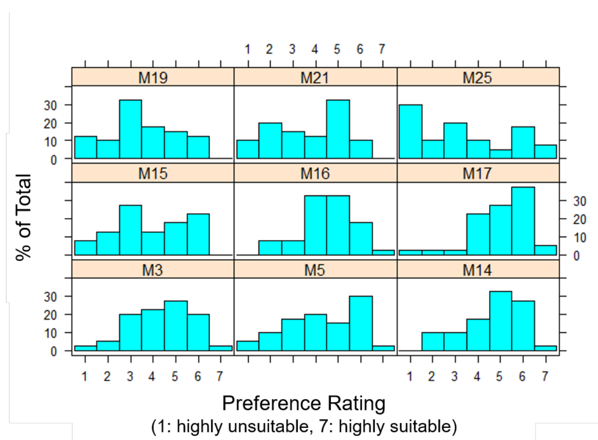


Figure 4: Frequency plot indicating the overall perceived suitability of each material tested. The vertical axis corresponds to the percentage of participants in the study.

5 DISCUSSION

The outcomes from the classification study (experiment 1), graphed in Figure 2, indicated that the 12 dimensions of texture (six adjective pairs) were each well represented by the 27 test materials. There was only one dimension, warm-cool, where the distribution of the data is observed to have a significant skew (towards warm textures). These results formed a dataset that may be useful to designers considering different materials for *robot-skin*, and also served to closely inform material selection in the second experiment.

An innovative aspect of the second part of the study was the use of VR to help participants visualize the service robot under consideration. Creating this immersive experience made it practical to use small material test samples, while also providing a stimulus to help inspire a suspension of disbelief during the experimental session.

The first research question set out to better understand the preferred stiffness characteristics of the surface material used on service robots. Interestingly, it was observed that in both exposure conditions, participants showed preference (at significant levels) for more compliant surfaces (medium/soft) over harder alternatives. While a thermoplastic was not tested directly in the second experiment, it is evident from Figure 2(c) that none of the shortlisted materials were perceived as being 'harder' than M20, which was chosen in the first experiment due to its close similarity to the plastic used on most existing service robot platforms. In light of this, it seems that stiff materials, like hard plastic, are not likely to provide the most suitable texture for *robot-skin*, at least from the perspective of tactile interaction. This conjecture is supported by the fact that nearly all the participants had little prior-familiarity with robots, indicating that subjective preferences were not likely to be primed by prior knowledge of existing robot systems. We think this is an interesting finding and hopefully one that will prompt further research.

The second research question considered if visualisation of the robot influenced the perceived suitability of the skin texture. The results revealed that for all but one of the materials, the perceived suitability was independent of whether the participants had a clear mental image of the robot or not. It is difficult to make any strong claims based on this finding, since only one robot was tested in the robot-visualization condition. However, if future studies reveal these findings to generalize to other robot embodiments, it may suggest that the preferred texture of *robot-skin* may not be dependent on the visual appearance of the robot it is deployed on.

The third research question investigated if any materials emerged as being especially well suited for use on service robots. Tests indicated that M17 and M14 were consistently deemed to be highly suitable, while M25 and M19 were generally deemed the least suitable. Examination of the contrasting characteristics of these perceived suitable and unsuitable materials draws some interesting insights. First, it is observed that M25, a material that was described in the free-form responses as 'fluffy', 'animal-like'and 'furry'was strongly disliked. This suggests that textures that are commonly deemed desirable for smaller therapeutic robots, may not be appropriate for service robots. Second, it would seem that the texture of *robot-skin* materials benefit from being smooth; both M17 and M14 were described as being 'smooth' in the free-form descriptions and both were rated in the top 30th percentile on smooth scale (Fig. 2(b)).

Interestingly, the most disliked materials rate on the extreme end of the scale in several textural dimensions; M25 is rated as extremely warm and complex, while M19 is most coarse, second most complex and second hardest. Contrasting both evaluations indicates that service robots may benefit from using skins that have a smooth texture, or at least avoid materials that might be polarising across several textural dimensions.

Finally, it is prudent to discuss these findings in the context of the limitations of the study. While steps were taken to improve the believably of the second experiment, VR can at best only provide an approximation for the real world. Similarly, while steps were taken to recruit participants that were not familiar with robots, factors such as the short participant briefing and testing period, the broad nature of some of the questions, and the lack of background context may have had an influence on some of the results. The authors also acknowledge that these experiments would benefit from greater use of qualitative methods, although steps were taken to ensure qualitative data collection methods were utilized. Despite these drawbacks, as an exploratory study, we believe that these findings provide compelling early evidence that the haptic experience of interacting with service robots may be improved if they are given more complex materials than the thermoplastics that have become the de facto standard in the industry.

6 CONCLUSIONS

The research presented in this study was driven by the desire to more fundamentally understand the social role of *robot-skin* in applications involving human-robot interaction. It was motivated by clear gaps in the research literature concerning touch in HRI and by considerable amount of anecdotal evidence that surface texture has been frequently overlooked by robot designers.

In the first of two experiments, we classified 27 materials that each had properties that could make them useful as an outer covering on a robot. Adopting six of the most widely used semantic differential scales previously used in the texture classification literature, each material was scored and ranked in relative order. Free-form responses describing the subjective impressions of each material were also recorded.

Using a representative sample of the previously classified materials, a second experiment was undertaken to investigate factors effecting the perceived suitability of different material combinations for applications as a *robot-skin*. Specifically, we focused on both the stiffness of the sample as well as the intrinsic properties of the surface material. We also investigated if subjective ratings were influenced by having a clear visualisation of the robot. The results indicated that test samples with soft-medium stiffness were preferred over samples with high stiffness. Our findings further indicate that having a clear visual image of the robot can effect perceptions of the most suitable *robot-skin* stiffness; this was less conclusive for the case of surface texture. In both cases, it is acknowledged that further research is necessary.

Finally, based on our findings, we identify a range of textural properties that seem to correlate with high and low suitability for use on service robots. It is hoped that these findings are useful to help inform the design of HRI systems, and motivate further investigation into the social roles of *robot-skin*.

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