# The concept of softness is structurally similar in memory, haptics, and vision

**Müge Cavdan** ( Muege.Cavdan@psychol.uni-giessen.de )
University of Giessen
**Nedim Goktepe**
Philipps University of Marburg
**Knut Drewing**
University of Giessen
**Katja Doerschner**
University of Giessen

**Article**

**Keywords:** memory, softness, haptics, prior knowledge, material perception

**Posted Date:** September 15th, 2022

**DOI:** https://doi.org/10.21203/rs.3.rs-2059871/v1

# Title: The concept of softness is structurally similar in memory, haptics, and vision

Authors and affiliations: Müge Cavdan[1*], Nedim Göktepe[2], Knut Drewing[1], Katja Doerschner[1,3]

[1]Justus Liebig University, Experimental Psychology, Gießen, 35390, Germany

[2] Philipps-University Marburg, Marburg, 35037, Germany

[3] National Magnetic Resonance Research Center, Ankara, 06800, Turkey

* Corresponding author

*Muege.Cavdan@psychol.uni-giessen.de

**Keywords:** memory, softness, haptics, prior knowledge, material perception

## ABSTRACT

Humans are very accurate and robust at recognizing materials (e.g., linen or hand cream) and estimating their properties (e.g., softness or stickiness). To achieve this, they rely on sensory input as well as on previous knowledge and experience. Softness is an important mechanical material property that can be perceived directly through haptic-, but also indirectly through visual inspection. While visual and haptic softness are similar we have found in previous work that there are also differences in how softness related material attributes are judged. Here, we investigate how softness memory relates to haptic and visual perceptual spaces of softness. We performed an online experiment where people rated different sensory aspects of soft materials, for which only names were presented, i.e., without any haptic or visual information about the material. We compared results with previous studies where identical ratings were made on the basis of visual and haptic information. Correlation and Procrustes analyses show that the description spaces for all materials were similar for verbal, haptic, and visual presentation. However, linear discriminant classifiers also unveiled subtle differences in how soft materials are represented and predicted from different types of information. Specifically, we found that memory better predicted visual than haptic softness.

## INTRODUCTION

The material qualities of objects influence how we interact with them, we tend to indent soft things, we grasp fragile things gently, and apply somewhat more force when a slippery surface starts to slide from our hands. To learn about materials, we usually explore them with our hands. Through such explorations, associations between visual and haptic perception are established, and this knowledge is important for guiding and shaping future interactions [1–10]. These associations are so strong that even when direct visual or haptic information is not available, we seem to be able to make statements about typical (or expected) material properties[11]. For instance, when we see the brand name of a hand cream, we may have certain expectations about the cream's viscosity, stickiness, smell, translucency, and color. All this information is available to us through our semantic knowledge of hand cream[12]. In fact, there are many examples in research demonstrating the existence of strong multisensory associations. For example, Adams et al.[13] showed that the glossiness of a surface can be used as a proxy for judging its slipperiness[13]. Similarly, Paulun et al.[14] showed that viscosity of liquids can be inferred from static images. In our own recent work, we showed that softness dimensions (viscosity, granularity, and surface softness[15]) that were derived from haptic rating experiments also apply to visually perceived materials in static (close-up images) and dynamic scenes (videos showing the manual exploration of materials)[15]. The high correspondence between static visual and haptic information suggests that, although the materials in the study were primarily defined through their mechanical and tactile properties, this information was also indirectly accessible through visual shape and texture cues alone. We argued that participants likely relied on their prior knowledge about the materials when rating tactile and mechanical properties, that is, the provided visual information activated the memory of a specific material, which allowed the participants to 'fill in' the 'missing' sensory information[15].

Yet, memory cannot only be used to fill in the blanks (i.e., supplement), it can also alter our perception. The memory color effect is one example where prior knowledge modulates color appearance[16–18]. The typical color of an object (e.g., bananas are yellow) influences the way people see an actual color. Similarly, Metzger and Drewing[19] found a memory softness effect: If participants believe that they probe the compliance of a harder material (e.g., a tennis ball) the same stimulus is perceived to be harder as compared to when they believe to probe a softer material (e.g., a sponge). Alley et al.[1] showed expectations based on prior knowledge about the typical kinematic properties of a material affect how material properties are perceived in static and dynamic scenes. In Cavdan et al.[15] we found that even by visual inspection alone people make reasonable judgements about haptic qualities (e.g., softness) of soft objects (e.g., sponge). This could be because interacting with many *sponges* of various soft qualities lead to the formation of memories of the material *sponge* which contains both visual and haptic properties. When we activate this specific semantic category (i.e., sponge) the typical visual and haptic properties of this material might be retrieved from memory.

Here we want to directly investigate this material memory component when participants judge softness-related qualities of materials, when neither visual nor haptic information is available. Softness is an important mechanical property of materials that is primarily perceived through touch[20–28], but can also be judged on the basis of visual information[29–35]. In a previous study[15] we showed systematic similarities as well as differences between visually and haptically perceived softness. Here we compare visual and haptic softness to softness memory. We conducted an online experiment where 132 participants rated material properties based on adjectives, that were also used in our previous work[3,15]. Materials were only presented as words, in order to conjure up a specific memory or concept. Using a Principal Component Analysis (PCA) we determined the dimensionality of the memory-derived perceptual softness space and compare it to those derived from our earlier haptic and visual experiments[3,15]. Results showed that memory-derived softness is a multidimensional construct, with similar perceptual dimensions as haptic and visual softness. We also used linear discriminant classification to test whether material ratings from memory can be used to correctly classify materials when actually being judged haptically or visually [3,15]. Classification analyses suggest that memory can be used to supplement softness-related material properties.

## RESULTS

### Perceptual softness space derived from memory

Our first aim was to determine the dimensionality of the softness space derived from memory and to compare it to those derived from earlier haptic and visual experiments. To this end, we first assessed interparticipant consistency of individual ratings of 19 materials (presented as words, see Table 1 and methods for trial details) using 15 adjectives to check to what extent participants responded similarly to the individual stimuli. Sufficiently high similarity in responses would allow us to use average material-adjective ratings across participants in the PCA. Bartlett scores of the PCA, which indicate how each material is associated with the extracted dimensions, were used in Procrustes analyses to measure the similarity between the perceptual softness space derived from memory with those derived from visual and haptic experiments. Since this analysis yielded a high agreement between conditions (memory [this experiment], visual [static and dynamic] and haptic), we submitted the average responses from each condition to a combined PCA in order to assess the more fine-grained structural differences between conditions. Numerical results of these analyses are reported next.

**Consistency**. Interparticipant correlations showed that only one of the participants was not consistent with all other participants ($r_{mean}$ = .20). We excluded this person from further analyses. Correlations between the remaining (131) participants were significant ($p$ < .001) and ranged between .30 and .82 ($r_{\mathrm{mean}}$ = .59) , and were similarly strong as in our earlier studies[3,15], This suggests, that participants share similar softness memory constructs for our stimuli, and allowed us to proceed with the PCA after averaging the rating data across participants.

**Dimensionality**. To determine the dimensionality of perceptual softness derived from memory we submitted the averaged ratings for the different materials to a covariance based principal component analysis (PCA). The Keyser-Meyer-Olkin (KMO) value was .53 and the Bartlett test of sphericity was significant, $\chi^2$ (105) = 344.70, $p < .01$, which suggests that it was appropriate to conduct a PCA. Principal components were extracted based on the Kaiser-criterion and rotated using the varimax method. Three extracted rotated components explained 82.87% of the total variance. The first component which we called *surface softness* (high adjective loadings from: *fluffy*, *hairy*, *velvety*, *soft*, and *hard*) accounted for 34.6% of the variance. The second component *viscosity* (adjective loadings: *wobbly*, *sticky*, *moist*, and *elastic*) accounted for 24.97% of the variance. Finally, the third component *granularity* (adjective loadings: *sandy*, *powdery*, *granular*, *rough*, and *smooth*) accounted for 23.28% of the variance. Table 1 shows the rotated adjective loadings for the memory experiment along with those, obtained from our previous visual and haptic experiments.

**Table 1.** Rotated adjective loadings for memory, static visual, dynamic visual, and haptic conditions. Colors indicate high adjective loads (> 40% of mean variance per adjective explained, which corresponds to loads of 0.64 memory, 0.68 static visual, 0.62 dynamic visual, 0.74 haptic), or that an adjective loads higher on a specific factor than on others. Bold if loading is positive, italic if the loading is negative.

| | Memory | | | Static | | | Dynamic | | | | Haptic | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Adjective | I. Surface softness (34.6%) | II. Granularity (23.28%) | III. Viscosity (24.97%) | I. Surface softness (38.2%) | II. Granularity (25.8%) | III. Viscosity (19.9%) | I. Surface softness (25.2%) | II. Granularity (23.7%) | III. Viscosity (21.8%) | IV. Deformability (18.5%) | I. Surface softness (25.9%) | II. Granularity (20.6%) | III. Viscosity (20.6%) | IV. Deformability (17.8%) | V. Roughness (9.5%) |
| Fluffy | **1.18** | -0.12 | -0.18 | **1.22** | -0.12 | -0.43 | **1.10** | -0.14 | -0.26 | -0.25 | **1.34** | -0.28 | -0.41 | -0.28 | 0.16 |
| Soft | **0.98** | -0.20 | 0.58 | **1.17** | -0.21 | 0.24 | **0.78** | -0.08 | 0.38 | -0.58 | **0.90** | -0.09 | 0.37 | -0.69 | -0.12 |
| Hairy | **0.96** | -0.03 | -0.28 | **0.84** | -0.10 | -0.41 | **0.83** | -0.10 | -0.27 | -0.15 | **1.07** | -0.39 | -0.25 | 0.06 | 0.48 |
| Velvety | **0.78** | -0.12 | 0.00 | **0.74** | -0.09 | -0.24 | **0.69** | 0.04 | -0.05 | -0.06 | **0.81** | 0.01 | -0.18 | -0.32 | -0.15 |
| Hard | *-0.77* | 0.30 | -0.58 | *-0.91* | 0.15 | -0.38 | -0.52 | 0.05 | -0.42 | **0.63** | -0.61 | 0.17 | -0.41 | *-0.91* | 0.09 |
| Sandy | -0.25 | **0.96** | -0.21 | -0.31 | **1.07** | -0.20 | -0.14 | **1.01** | -0.10 | 0.27 | -0.15 | **1.14** | -0.12 | 0.28 | 0.25 |
| Granular | -0.56 | **0.95** | -0.32 | -0.55 | **1.03** | -0.20 | -0.29 | **0.90** | -0.18 | 0.55 | -0.41 | **1.10** | -0.03 | 0.68 | 0.22 |
| Powdery | -0.17 | **0.70** | -0.09 | -0.20 | **0.94** | -0.07 | -0.05 | **0.92** | -0.02 | 0.28 | -0.06 | **0.97** | -0.05 | 0.17 | 0.10 |
| Rough | -0.20 | **0.74** | -0.39 | -0.41 | **0.76** | -0.39 | -0.30 | 0.54 | *-0.57* | -0.02 | -0.39 | 0.38 | -0.33 | 0.14 | **0.70** |
| Smooth | -0.23 | *-0.57* | 0.03 | -0.38 | *-0.61* | 0.09 | -0.13 | *-0.50* | 0.23 | 0.30 | -0.27 | -0.20 | 0.11 | 0.12 | *-0.95* |
| Sticky | -0.20 | -0.16 | **0.94** | -0.12 | -0.13 | **0.98** | -0.18 | -0.03 | **0.88** | -0.12 | -0.26 | 0.04 | **1.11** | -0.16 | -0.08 |
| Moist | -0.13 | -0.03 | **0.88** | -0.11 | -0.16 | **0.91** | -0.15 | -0.19 | **0.99** | -0.02 | -0.12 | 0.03 | **1.14** | 0.05 | -0.25 |
| Wobbly | 0.06 | -0.25 | **0.74** | 0.18 | -0.27 | **0.78** | -0.13 | -0.16 | **0.70** | -0.42 | 0.03 | -0.22 | **0.96** | -0.40 | -0.04 |
| Elastic | 0.36 | -0.31 | **0.61** | **0.62** | -0.33 | 0.39 | 0.11 | -0.19 | 0.17 | *-0.75* | 0.10 | -0.32 | 0.28 | **0.80** | 0.09 |
| Inflexible | -0.41 | 0.18 | -0.41 | *-0.72* | 0.33 | -0.21 | -0.30 | 0.27 | 0.00 | **0.75** | -0.24 | 0.43 | 0.07 | *-0.84* | -0.04 |

It appears that the adjective loadings obtained from the memory experiment were most similar to those obtained from the static visual condition. Overall, the extracted components and loading patterns were similar to those obtained in our previous haptic and visual softness studies (see Cavdan et al.,[15]), where we found that *surface softness*, *granularity*, and *viscosity* were common to all haptic & static and dynamic visual conditions and explained most of the variance in ratings, whereas *deformability* only appeared in the dynamic visual and haptic conditions. Finally, roughness was only specific to the haptic condition[15].

In order to quantitatively assess the similarities between the three common components (surface softness, granularity, and viscosity) across memory, haptic, and the two visual spaces we performed a Procrustes analysis on the Bartlett scores of materials. From this analysis we calculated the sum of squared errors that remains after mapping between any two spaces.

Overall, the error between conditions was low (memory and static visual: .12, memory and dynamic visual: .32, memory and haptic: .33) which indicates a good fit between the four softness spaces [36]. We used a bootstrapping approach[37] for significance testing. First, for every space comparison, we created 10000 pseudo Bartlett values by shuffling the respective empirical Bartlett values. Then, we calculated the Procrustes error for each empirical and pseudo comparisons. All empirical mapping errors were significantly lower than chance as they were within the first 2.5 percentile of the pseudo errors (equivalent of two-tail significance test with $\alpha = 0.05$), meaning that the softness spaces were significantly similar to each other.

**Memory, vision, haptics – combined perceptual softness space**

After confirming the similarity between semantic, haptic, static visual, and dynamic visual spaces we conducted a combined PCA. This would help us to determine fine-grained differences between structural similarities or differences in the spaces. Mean ratings from all four condition were submitted to a single PCA. The KMO value was .71 and Bartlett's test of sphericity was significant, $\chi^2$ (105) = 1550.73, $p < .01$ suggesting that PCA was suitable for the averaged rating data across four conditions. Then we extracted the principle components for the combined data based on Kaiser-criterion and rotated them, using the varimax method. Four components accounted for 87.98% of the total variance (see Table 2). The first component, labelled *surface softness,* accounted for 30.50% of the variance. Adjectives loading high on this component were *fluffy*, *velvety*, *soft*, *hairy*, and *hard*. The second component, labelled *granularity,* accounted for the 26.52% of the variance. Here, the adjectives *powdery*, *sandy*, *granular*, *inflexible*, and *elastic showed high loading*. On the third component, which accounted for 22.25% of the variance, adjectives *sticky*, *moist*, and *wobbly* loaded highly and was thus labelled *viscosity*. Finally, the component labelled *roughness* explained 8.71% of the variance. On this component only the adjective *rough* and *smooth loaded highly.*

**Table 2.** Rotated adjective loadings from the combined PCA analysis. Components determined based on high adjective loadings (>40% of the mean variance corresponding to loading .66 or highest on a specific dimension). Bold if loading is positive and italic if loading is negative.

| Adjective | I. Surface softness | II. Granularity | III. Viscosity | IV. Roughness |
|---|---|---|---|---|
| Fluffy | **1.19** | -0.25 | -0.34 | -0.10 |
| Velvety | **0.82** | -0.06 | -0.09 | 0.11 |
| Soft | **1.02** | -0.30 | 0.45 | -0.09 |
| Hairy | **0.83** | -0.22 | -0.37 | -0.20 |
| Hard | *-0.73* | 0.40 | -0.51 | 0.22 |
| Powdery | -0.06 | **0.88** | -0.03 | -0.19 |
| Sandy | -0.16 | **1.03** | -0.12 | -0.30 |
| Granular | -0.41 | **1.10** | -0.19 | -0.11 |
| Inflexible | -0.41 | 0.57 | -0.22 | 0.35 |
| Elastic | 0.32 | *-0.52* | 0.44 | -0.30 |
| Sticky | -0.16 | -0.05 | **0.96** | 0.10 |
| Wobbly | 0.04 | -0.29 | **0.82** | -0.02 |
| Moist | -0.12 | -0.04 | **0.94** | 0.23 |
| Smooth | -0.16 | -0.22 | 0.13 | **0.76** |
| Rough | -0.37 | 0.48 | -0.40 | *-0.57* |

Next, with correlation analyses we directly tested the similarity between the memory - and other three conditions. To this end, Bartlett values of each condition were calculated from the combined PCA. A Bartlett value is the score that shows the loading of a material in each dimension (i.e., hand cream loading score per *surface softness*, *granularity, viscosity,* and *roughness*). The scores that are obtained from each condition are correlated with the memory scores (i.e., memory-haptic, memory-static, memory-dynamic).

All correlations were significant at $p < .001$ level (Bonferroni-corrected for three tests). Fig. 1 shows the correlations between the extracted Bartlett scores of the four softness spaces: memory-haptic ($r = .88$), memory-static ($r = .92$), and memory-dynamic ($r = .90$). These strong correlations indicate high similarity between memory and perception-based description spaces.

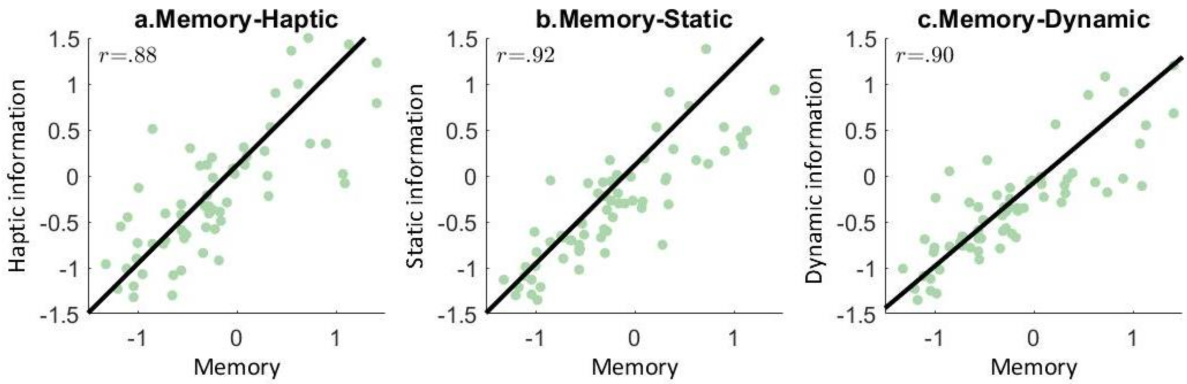


**Figure 1.** Scatter plots of the correlation's coefficients of Bartlett scores, correlation coefficients between conditions: **a.** memory-haptic **b.** memory-static visual **c.** memory-dynamic visual.

**Prediction of Material Softness from Different Domains**

PCA and Procrustes analysis showed that also memory softness – a softness space which is derived from memory – is a multidimensional construct and overall similarly organized as haptic, static visual, and dynamic visual softness. Such a differentiated softness space in memory could allow to supplement information when perceptual material information is ambiguous or missing. Here we tested to what extend visual and haptic softness can be predicted from memory softness. Predicting softness information could be realized at a coarse level through material dimensions (e.g., granular materials). That is to say, it could be possible to predict material granularity information from memory when one is asked to judge properties of granular materials.

We tested this possibility of predicting material categories at a coarse level (i.e., material dimensions: granular, surface soft, viscous materials) by training a linear discriminant classifier (6-fold validation) for each condition (i.e., static visual, dynamic visual, haptic) to predict memory and vice versa. Each classifier was trained on adjective ratings of materials that loaded high in one of the three softness dimensions (see Supplementary Fig. 3). Specifically, we used the ratings from the following materials; surface softness: velvet, fur, and cotton balls; granularity: salt and sand; viscosity: hand cream and hair gel.

The results in Fig. 2 shows, that overall, classifiers performed better than chance (chance level = 100/3 = 33.3). The classifiers trained on visual and memory conditions predicted visual and memory conditions almost perfectly (all accuracies > 99%). However, prediction of the haptic condition from the visual or memory conditions and vice versa was lower (~45% accuracy, see Fig.2).

More specifically, the classifier trained in haptic data frequently confused *surface softness* with *granularity* and *viscosity*, and confused *viscosity* with *surface softness* when classifying the softness dimensions of materials based on their ratings from memory (Fig. 2), and visual conditions (Supplementary Fig. 1).

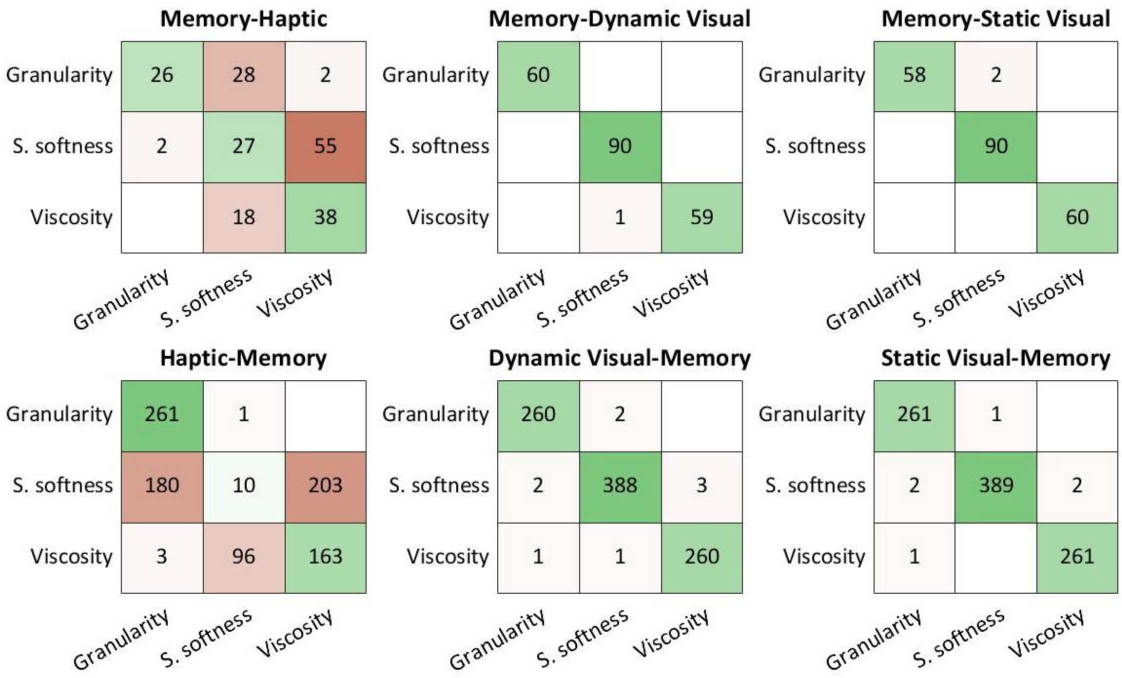


**Figure 2.** Confusion matrices showing the softness dimension classification performance of Static, Memory, Haptic, and Dynamic linear discriminant classifiers trained on adjective ratings in the respective conditions. Material classification performances as follows. **Memory classifier**: Haptic: 46.43%, Dynamic: 99.52%, Static: 99.05%. **Haptic classifier**: Memory: 36.42%, **Dynamic classifier**: Memory: 99.02%, **Static classifier**: Memory: 99.35%. x-axes show the predicted dimension while y-axes show the true dimension.

Taken together, the Procrustes analysis on Bartlett values of materials across common softness dimensions showed that material softness is mapped similar in haptic, memory, and visual domains, and the linear discriminant classifiers showed that for the most part the three common perceived dimensions softness are also classifiable across sensory and memory domains. However, high similarity in softness representations only suggest that softness maps (i.e., extracted softness spaces from memory, vision, and haptics) are organized similarly enough to allow supplement across domains. This explains, for example, why we imagine the feel of viscosity when we see a hair gel commercial and not granularity. However, being able to infer how a hair gel exactly feels on hand from a picture requires corresponding multisensory representation of hair gel's soft qualities in memory, visual, and haptic domains. The material mapping errors in Procrustes analysis show that individual materials are similarly mapped across conditions. Thus, one could argue that if a material can be classified by its softness properties in one domain then it should also be classifiable in another domain. This would imply that not only sensory and memory softness representations are highly similar, but soft qualities of materials are represented closely enough to identify materials and possibly supplement missing information to infer their otherwise unavailable soft qualities.

To test this hypothesis, we trained a second set of linear discriminant classifiers for each condition, again using the adjective ratings of the materials that are highly loaded to one softness dimension (i.e., sand) to directly classify materials in other conditions (6-fold validation). The classifiers trained on memory, static visual, and dynamic visual data were able to make cross-condition material classifications better than chance (Chance level = 100/7 = 14.29%). Although significant, the cross-classification performance of the classifier trained on haptic may be negligible as it could reliably classify only *hand cream* in other conditions. Whereas, other classifiers were not able to classify the materials by haptic qualities. The classification errors were due to confusing materials that are dominantly represented in the same softness dimension (e.g., hair gel and hand cream, both are *viscous* materials).

Overall, performances of visual and memory support the idea that softness information in these domains can predict and supplement each other.

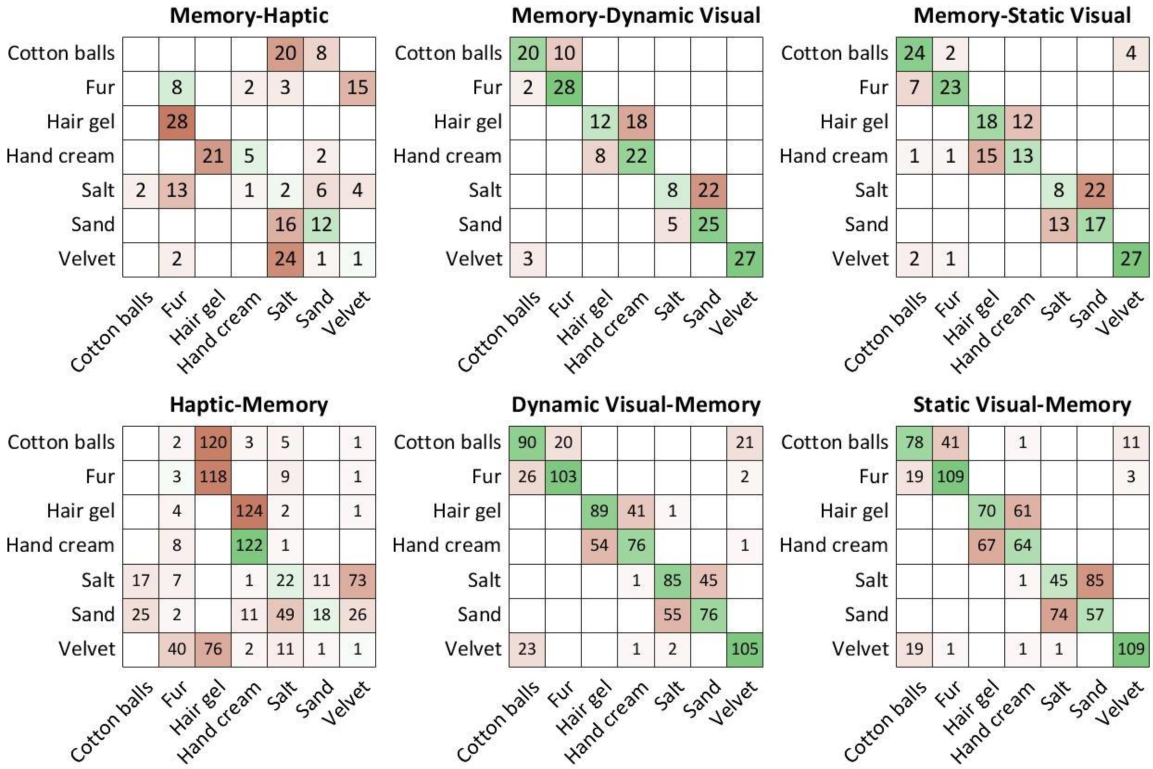


**Figure 3.** Confusion matrices showing the material classification performance of Static, Semantic, Haptic, and Dynamic linear discriminant classifiers trained on material ratings in respective conditions. Material classification performances as follows. **Memory classifier**: Dynamic: 67.62%, Haptic: 14.29%, Static: 61.9%. **Haptic classifier**: Memory: 18.1%. **Dynamic classifier**: Memory: 68.05%. **Static classifier**: Memory: 58.02%. Numbers in each row add up to number of materials representing each dimension x number of participants in each classified condition.

## Discussion

In our daily lives we interact with a vast range of materials, and this interaction generates multisensory information. Our perception, categorization, and interaction with materials are not only determined by this rich sensory information but also by our previous interactions with, and by our knowledge about a given material. In the current study, we tested whether memory-derived softness dimensions are similar to perceived softness from haptic explorations, from visual images, or from movies of someone else exploring materials. Importantly, we found that, also memory of soft materials is represented by a multidimensional construct, that is highly similar to that obtained from visual and haptic conditions[29,36,38,39,11], where judgements were found to vary along surface softness, granularity, and viscosity.

Through the basic structures of separately extracted perceptual spaces, correlations, and Procrustes analysis we showed that memory softness is judged slightly more similarly to visual static and visual dynamic softness compared to haptic softness. Specifically, the classification performances indicated that softness dimensions as well as specific materials are well predictable by softness judgments from memory to visual conditions and vice versa, but not to the same degree from memory to haptic conditions and vice versa (see also Supplementary 1). This is quite surprising, given that softness can be directly estimated from the physical properties of materials, while visual and memory softness are associative[11]. Therefore, one would expect haptic softness to be more similar to other conditions, since those spaces should be derived from haptic softness. Conversely, it could be argued that the visual and memory should be more similar to each other than haptic, since the latter can be used to estimate softness without depending on supplemental information from memory. Nevertheless, similarly organized softness representations may allow supplement at least across memory and visual domains where it is mostly needed. Future studies could directly study multisensory supplementing of softness by comparing the softness judgments of familiar and novel materials under ambiguous or impoverished sensory conditions.

Participants in our previous studies[3,15] judged the softness of materials through haptic or visual exploration, whereas in the current study, they only saw the written name of the materials. Therefore, their judgments were not dependent on direct visual or haptic information but instead on their knowledge and experience[11]. This might have created more variance in participants' judgments, however, we found high agreement between participants' softness judgements, suggesting that perceived softness dimensions were very similar across individuals, and that the softness construct for the memory materials were shared across participants. This similarity might be explained by the fact that the materials we used, were very familiar in the studied population. Using more diverse and less frequently used materials, might have led to different results.

## Memory Softness as a Multidimensional Construct

Previously, we have shown that visually and haptically perceived softness is represented in highly similar multidimensional spaces with some fine-grained differences[15]. Building upon this we tested here, whether the knowledge of soft materials as triggered by the materials' names (i.e., memory) has the same multidimensional structure. Participants were consistent in judging different qualities of soft materials from their names alone (cf. also[11]). Similarities in the descriptive space of the material properties (from PCAs) from haptic, static visual, dynamic visual, and memory conditions suggest that memory and perceptual representations of softness are related: Haptic, static visual, dynamic visual, and memory of softness maps into shared *granularity*, *surface softness*, and *viscosity* dimensions. In addition, when comparing knowledge-based softness ratings and Bartlett scores with that from sensory condition we find strong positive correlations and good fits in Procrustes analyses. The high correspondence between memory, visual, and haptic softness information may be arising from a common softness mapping that represent softness information across modalities. Alternatively, the high correspondence we observed can be explained by multiple similarly organized softness maps that represent softness information from different modalities. In this scenario, it could be that softness is primarily perceived and represented by (remembered) touch. However, this representation is closely followed by secondary domains such as vision and memory through associations and experience. The differences we observed in the dimensional structure of PCAs between haptic and memory/static visual conditions appears to support the latter option. While static visual and memory spaces resulted in only three dimensions (i.e., *surface softness*, *granularity*, and *viscosity*), deformability emerged in both haptic and dynamic conditions. The features people use to represent knowledge seems not only to consist of low-level image cues but seems to also include physical and mechanical properties of materials such as *viscosity*, *softness*, and *surface softness*[1].

However, interestingly, in the memory and static visual conditions the mechanical properties seem to exclude deformability. One possible explanation for this could be that people simply rely on static visual knowledge of materials when judging softness from names. Another possibility is that people rely on the same knowledge in static visual and memory conditions. Deformability is a kinematic property which can be obtained from dynamic shape and texture cues[33,40,41] or material knowledge. If an assessment of a specific material attribute has not been made earlier, that information will be missing which might be the case for some attributes, such as accessing elasticity of hand cream. In contrast, dynamic visual input can provide information about the deformability of the materials[1,33,40,42,43], especially if manual explorations of the materials can be observed (or made directly) [15,34,44].Taken together, we find that the softness space obtained from the memory condition is most similar to that obtained from the static visual condition. Both of these conditions might be lacking dynamic information that is readily available in dynamic vision and haptics.

## Supplementing Softness Information

When judging material properties, sensory information from one sense can be insufficient or ambiguous. In such a case, sensory information from other senses can be drawn upon[13,14], or memory of and prior experiences with materials[45] can be used to make a given inference about a material property. However, in order to make inferences  the mapping between sources of information needs to be well-defined. For instance, if visual gloss can indicate haptic slipperiness[13], visual gloss values need to be mapped to haptic slipperiness values in the perceptual system. Previous research seems to suggest that this might be the case. For example, Baumgartner et al. [29] have shown that major visual and haptic material dimensions are highly corresponding. In the current and a previous study[15], we extended this finding by showing similar softness dimensions underly the softness representation of haptic, memory, static visual, and dynamic visual materials, and that materials were similarly represented across these conditions.

We argued that one function of having corresponding representations could be to allow to supplement softness information from other domains, especially memory. The high similarity in static and dynamic visual conditions[15] and memory could allow supplementing missing dynamic information in static visual scenes. This can be seen from participants' ability to judge viscosity of liquids from static images[14]. These judgments are well explained by shape cues. The ability to infer viscosity from shape cues might be attributed to the similarity between dynamic and static visual spaces. Alternatively, previous dynamic experience with liquids could explain this ability. In this case, corresponding representations of softness determine how much of the softness information can be recovered from memorized sensory information triggered by the available cues indicating the same material. In this case, correctly identifying a material through sensory or memory cues allow the recovery of remaining properties of the material. However, based on the present data we cannot distinguish between these two options. In both cases, possessing highly similar material presentations across softness spaces is highly useful for accessing rich information that may not be available to senses.

We tested whether having a similar softness representations provides utility for predicting softness dimensions between memory and the haptic and two visual conditions. The first set of linear classifiers trained on classifying *granularity*, *surface softness*, and *viscosity* of the materials showed that visual, haptic, and memory information on these dimensions is not only similar but also, can be used to classify softness information in other conditions with systematic differences reflecting the differences among softness spaces. However, it is important to note there the classification performances with haptic information was much lower than visual and memory classification performances. The systematic difference in classification performances for the haptic condition echoes the differences in adjective loadings in haptic condition compared to the other three (Table 1). This suggests there are subtle differences between haptic and other conditions in terms of how materials are represented by these softness dimensions. Despite of these differences, the first set of classifiers show that highly similar multisensory softness mapping between haptic, vision and memory allows to make coarse inferences at the dimension level about material properties using the cues available in these modalities. These corresponding perceptual dimensions might provide the foundation for coarsely judging the softness of materials from a large pool of sensory memory or cues that are present in the environment.

Quickly recognizing and placing materials to perceptual dimensions is important to shape our initial way of interaction with objects[46]. However, the way we interact with materials needs to be more fine-tuned since materials that are similarly represented in perceptual spaces might still have distinct properties. For instance, softness of a thin glass or a metal cup might be mapped more similarly than softness of a velvet but we would handle the thin glass more similarly to a velvet cloth than a metal cup. Therefore, supplementing specific material properties from the available sensory cues is necessary. The second set of classifiers trained for material classification showed that softness information gathered from memory, visual static, and visual dynamic information can be used to classify materials across these conditions. This high correspondence in softness representations between memory and visual conditions may allow coarse predictions at the dimensional level as well as direct material categorization.

While confusions within the same softness dimension are in line with previous findings[11], we explain the differences between haptic and other conditions by the higher correspondence between visual and memory conditions than haptic condition. For instance, it appears that *surface softness* in haptics is mapped differently than *surface softness* in other conditions. This discrepancy between haptics and the visual conditions might be explained by our daily exploration habits. In daily life, we usually explore fine structures not by closely looking as in close-up pictures but by touch in close contact. In line with this, Rakhin & Onkar[47] found strong positive correlation between haptic and visual exploration of textiles in terms of smoothness when close-up high resolution images are presented. However, this relationship between haptics and vision was weaker for the full image of the textiles. This might mean that, some fine-tuned visual texture information can only be captured with the optimal viewing distance. In the current study even though the close-up images were used in the static visual and close-up videos in the dynamic visual condition, these might still lack critical visual cues that would bring the visual conditions closer to the haptic condition.

The confusion errors of the material classifiers could help us understand the characteristics of supplementing softness information (see Fig. 3). For instance, when a material is misclassified, it is usually confused with another material that has high values on the same softness dimension. Moreover, material classification errors (Fig. 3) followed the dimension classifiers (Fig. 2), for example, we find in Fig. 2 that the dimensions of *surface softness* and *viscosity* were confused and similarly hairy and viscous materials were confused. This further supports that common dimensions underly the perceptual space of material softness: materials that are similarly mapped in these dimensions were also easier to confuse with each other.

## Conclusion

In conclusion, people are consistent and reliable at judging softness from memory. The memory softness is similar to haptics, static visual, and dynamic visual spaces with the common dimensions of *granularity, viscosity,* and *surface softness*. The classification performances suggest that softness information from memory, visual static, and visual dynamic domains are well suited to supplement softness information when the sensory information is insufficient. Moreover, tight mapping of materials in softness spaces is crucial as it allows supplement material information evidenced by material classification across softness spaces. Finally, while our analysis suggests high correspondence across softness spaces they also pointed out subtle differences.

## Methods

### Participants

A total of 132 students from Giessen University took part in the online experiment (96 female, 36 male, $M_{age}$: 21.6). An additional 90 students participated in the previously reported conditions (static visual condition: 20 females, 10 males; $M_{\mathrm{age}}$ = 23.4, age range: 20-31; dynamic visual condition: 21 females; age range: 20-33; $M_{\mathrm{age}}$ = 25.1; haptic condition: 21 females, 9 males; $M_{\mathrm{age}}$: 23.6, age range: 18-38). All participants in the static visual, dynamic visual, and haptic conditions were right-handed according to self-reports. Participants in the haptic condition reported no sensory, motor, or cutaneous impairments. Participants in the visual conditions had normal or corrected-to-normal visual acuity and normal color vision[48]. The study was ethically approved by Local Ethics Committee of Faculty 06 at Justus Liebig University Giessen in accordance with Helsinki declaration[49] except for pre-registration.

Participant gave written informed consent before the experiments. All participants received either 8 €/h or course credits for their participation.

## Stimuli

Materials and adjectives were the same as Cavdan et al.[3]. Materials were chosen to score high on their respective dimension, adjectives were select to represent these dimensions (i.e., surface softness, granularity, viscosity, deformability, and roughness). The full list of material names and their corresponding dimensions are: deformability (sponge and playdough), viscosity (hand cream and hair gel), furriness (velvet, fur, and cotton balls), granularity (sand and salt), roughness (sandpaper and felt), control (stress balls, cranberries, aluminum foil, linen, lentils, pebbles, paper balls, and wool). The full list of adjectives and the corresponding dimensions are as follows: furriness (fluffy, hairy, soft, and velvety), viscosity (moist, sticky, and wobbly), granularity (granular, sandy, and powdery), deformability (hard, inflexible, and elastic), and roughness (rough and smooth). In the haptic experiment, the roughness dimension has been used as a control dimension[3] in order to test the validity of the experimental paradigm, because this dimension is well validated in active touch.

As already mentioned, the same materials and adjectives were used as in the previous haptic and visual experiments[3,15]. Below we briefly summarize how they were previously presented: 19 real materials were used in the haptic experiment. Participants freely explored these materials while we recorded their hand movements. For the previous static visual condition still images were taken for all 19 materials which were placed on a green fabric. Traces of hand explorations were left whenever possible (e.g., run through marks for salt) in order to increase the availability of shape cues. Close-up images were taken at 3840 × 2160 pixels resolution which was reduced to size of 2049 × 1464 pixels after postprocessing. For the previous dynamic visual condition, previously recorded manual explorations of real materials were used.

During manual explorations we found that people adapt hand movements based on material, task, and the interaction between material and task[3] . Thus, combination of two hand movements are preferred while exploring some materials and one hand movement is preferred while exploring the others. For instance, people frequently used run thorough in combination with rotate while exploring granular materials while using only rubbing for furry materials. Therefore, the most frequent one or two hand movements were determined and movies following those patterns were selected randomly. For each material, videos of three different people were selected in order to avoid biases from individual exploration styles. Videos were video clips of 6 seconds (180 frames) with the resolution at 1012 × 1080 pixels. The resulting video set consisted of 57 videos (19 materials × 3 sets). Details of the movies and still images can be found in Cavdan et al.[15].

**Design and Procedure**

An online experiment was conducted (using testable.org) to test how people judge softness of different materials from only memory information. In the beginning of the experiment participants received written instructions stating that they would be receiving a list of adjectives describing different material qualities. In each trial an adjective was presented on the participant’s screen for two seconds followed by a material name. Participants rated how much that adjective applies to the material on a five-point scale (1: does not apply, 5: strongly applies). The order of adjectives and materials was randomized. The same procedure was followed in the previous haptic and visual studies with the differences only in the stimulus presentation (see Fig. 4). In the visual static condition, participants pressed the space button after the adjective had been presented. Then an image appeared and stayed on the screen for 2 seconds. In the dynamic visual condition, after pressing the space button, a manual exploration video was presented. In the haptic experiment, after pressing the space button, a beep sound signaled the start of 4 seconds exploration duration and participants freely and actively explored the materials. During the exploration their vision was blocked with a curtain. Another beep signaled the end of exploration period and participant asked to disengage the exploration. The task of the participant was always to rate the applicability of an adjective to the presented material.

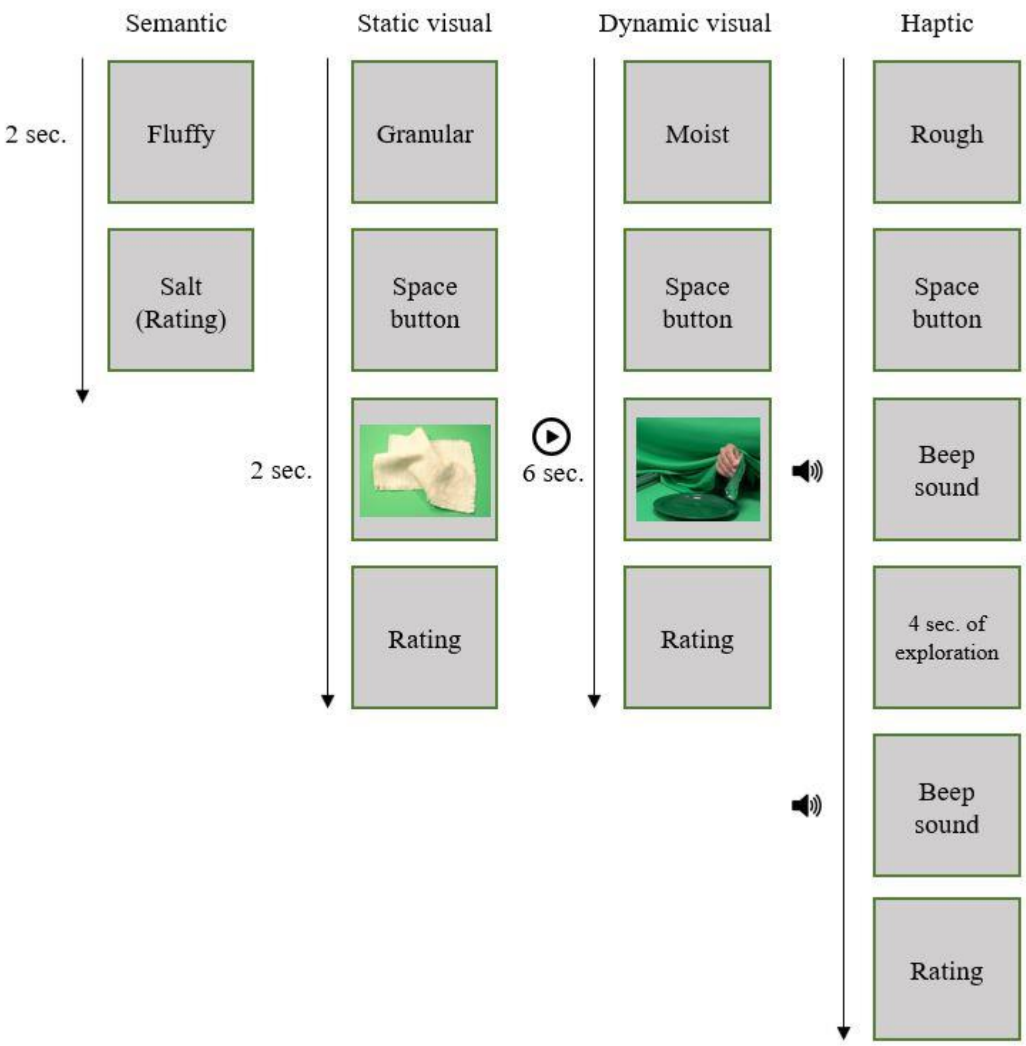


**Figure 4.** Time course of a trial across conditions. In all conditions, an adjective to be rated was presented on the screen first. After pressing a button, the name of a material is presented on the screen for 2 seconds in the semantic, a static image presented in the static visual, a 6 second movie clip showing manual exploration is presented in the dynamic visual condition. In the haptic condition, a beep sound signaled the start of 4 seconds of exploration, and another

beep signaled the end of the trial. In all conditions, participants indicated how much a given adjective applies to the material on 5-point Likert scale.


## Acknowledgements

We would like to thank Christoph Driftmann for the data collection and Roland W. Fleming for the fruitful discussions. Research was supported by the EU Marie Curie Initial Training Network "DyVito" (H2020-ITN, Grant Agreement: 765121), Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – project number 222641018 – SFB/TRR 135, A5 and B8. N.G. was supported by the German-Canadian International Research Training Group (IRTG) 1901 "Brain in action" by the German Research Foundation (DFG).


## Author contributions statement

M.C., K.D., and K.D. conceived and conducted the study, M.C. and N.G. analyzed the results and wrote the manuscript. All authors reviewed the manuscript.

## Data availability

The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

## References

1. Alley, L. M., Schmid, A. C. & Doerschner, K. Expectations affect the perception of material properties. *J Vis* (2020) doi:10.1167/jov.20.12.1.

2. Callier, T., Saal, H. P., Davis-Berg, E. C. & Bensmaia, S. J. Kinematics of unconstrained tactile texture exploration. *J Neurophysiol* (2015) doi:10.1152/jn.00703.2014.

3. Cavdan, Doerschner & Drewing. Task and material properties interactively affect softness explorations along different dimensions. *IEEE Trans Haptics* (2021) doi:10.1109/TOH.2021.3069626.

4. Fei-Fei, L., Fergus, R. & Perona, P. A Bayesian approach to unsupervised one-shot learning of object categories. in *Proceedings of the IEEE International Conference on Computer Vision* (2003). doi:10.1109/iccv.2003.1238476.

5. Fei-Fei, L., Fergus, R. & Perona, P. One-shot learning of object categories. *IEEE Trans Pattern Anal Mach Intell* (2006) doi:10.1109/TPAMI.2006.79.

6. Lake, B. M., Salakhutdinov, R. & Tenenbaum, J. B. Human-level concept learning through probabilistic program induction. *Science (1979)* (2015) doi:10.1126/science.aab3050.

7. Lake, B. M., Salakhutdinov, R. & Tenenbaum, J. B. One-shot learning by inverting a compositional causal process. in *Advances in Neural Information Processing Systems* (2013).

8. Morgenstern, Y., Schmidt, F. & Fleming, R. W. One-shot categorization of novel object classes in humans. *Vision Res* (2019) doi:10.1016/j.visres.2019.09.005.

9. Paulun, V. C., Gegenfurtner, K. R., Goodale, M. A. & Fleming, R. W. Effects of material properties and object orientation on precision grip kinematics. *Exp Brain Res* (2016) doi:10.1007/s00221-016-4631-7.

10. Tommasi, T. & Caputo, B. The more you know, the less you learn: From knowledge transfer to one-shot learning of object categories. in *British Machine Vision Conference, BMVC 2009 - Proceedings* (2009). doi:10.5244/C.23.80.

11. Fleming, R. W., Wiebel, C. & Gegenfurtner, K. Perceptual qualities and material classes. *J Vis* (2013) doi:10.1167/13.8.9.

12. Gärdenfors, P. Semantic Knowledge, Domains of Meaning and Conceptual Spaces. in (2017). doi:10.1007/978-3-319-44588-5_12.

13. Adams, W. J., Kerrigan, I. S. & Graf, E. W. Touch influences perceived gloss. *Sci Rep* (2016) doi:10.1038/srep21866.

14. Paulun, V. C., Kawabe, T., Nishida, S. & Fleming, R. W. Seeing liquids from static snapshots. *Vision Res* (2015) doi:10.1016/j.visres.2015.01.023.

15. Cavdan, M., Drewing, K. & Doerschner, K. The look and feel of soft are similar across different softness dimensions. *J Vis* (2021) doi:10.1167/jov.21.10.20.

16. Witzel, C. An easy way to show memory color effects. *Iperception* (2016) doi:10.1177/2041669516663751.

17. Witzel, C., Olkkonen, M. & Gegenfurtner, K. R. Memory colours affect colour appearance. *Behav Brain Sci* (2016) doi:10.1017/S0140525X15002587.

18. Witzel, C., Valkova, H., Hansen, T. & Gegenfurtner, K. R. Object knowledge modulates colour appearance. *Iperception* (2011) doi:10.1068/i0396.

19. Metzger, A. & Drewing, K. Memory influences haptic perception of softness. *Sci Rep* (2019) doi:10.1038/s41598-019-50835-4.

20. Caldiran, O., Tan, H. Z. & Basdogan, C. Visuo-Haptic Discrimination of Viscoelastic Materials. *IEEE Trans Haptics* (2019) doi:10.1109/TOH.2019.2924212.

21. Higashi, K., Okamoto, S., Yamada, Y., Nagano, H. & Konyo, M. Hardness perception based on dynamic stiffness in tapping. *Front Psychol* (2019) doi:10.3389/fpsyg.2018.02654.

22. Higashi, K., Okamoto, S., Yamada, Y., Nagano, H. & Konyo, M. Hardness perception by tapping: Effect of dynamic stiffness of objects. in *2017 IEEE World Haptics Conference, WHC 2017* (2017). doi:10.1109/WHC.2017.7989853.

23. Lederman, S. J. & Klatzky, R. L. Hand movements: A window into haptic object recognition. *Cogn Psychol* (1987) doi:10.1016/0010-0285(87)90008-9.

24. Klatzky, R. L., Lederman, S. J. & Metzger, V. A. Identifying objects by touch: An "expert system." *Percept Psychophys* (1985) doi:10.3758/BF03211351.

25. Okamoto, S., Nagano, H. & Yamada, Y. Psychophysical dimensions of tactile perception of textures. *IEEE Trans Haptics* **6**, 81–93 (2013).

26. Srinivasan, M. A. & LaMotte, R. H. Tactual discrimination of softness. *J Neurophysiol* (1995) doi:10.1152/jn.1995.73.1.88.

27. Xu, C., Wang, Y., Hauser, S. C. & Gerling, G. J. In the tactile discrimination of compliance, perceptual cues in addition to contact area are required. in *Proceedings of the Human Factors and Ergonomics Society* (2018). doi:10.1177/1541931218621347.

28. Xu, C., Wang, Y. & Gerling, G. J. An elasticity-curvature illusion decouples cutaneous and proprioceptive cues in active exploration of soft objects. *PLoS Comput Biol* (2021) doi:10.1371/JOURNAL.PCBI.1008848.

29. Baumgartner, E., Wiebel, C. B. & Gegenfurtner, K. R. Visual and haptic representations of material properties. *Multisens Res* (2013) doi:10.1163/22134808-00002429.

30. Bi, W. & Xiao, B. Perceptual constancy of mechanical properties of cloth under variation of external forces. in *Proceedings of the ACM Symposium on Applied Perception, SAP 2016* (2016). doi:10.1145/2931002.2931016.

31. Drewing, K., Ramisch, A. & Bayer, F. Haptic, visual and visuo-haptic softness judgments for objects with deformable surfaces. in *Proceedings - 3rd Joint EuroHaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems, World Haptics 2009* (2009). doi:10.1109/WHC.2009.4810828.

32. Klatzky, R. L. & Wu, B. Visual-Haptic Compliance Perception. in (2014). doi:10.1007/978-1-4471-6533-0_2.

33. Schmid, A. C. & Doerschner, K. Shatter and splatter: The contribution of mechanical and optical properties to the perception of soft and hard breaking materials. *J Vis* (2018) doi:10.1167/18.1.14.

34. Wijntjes, M. W. A., Xiao, B. & Volcic, R. Visual communication of how fabrics feel. *J Vis* **19**, 1–11 (2019).

35. Xiao, B., Bi, W., Jia, X., Wei, H. & Adelson, E. H. Can you see what you feel? Color and folding properties affect visual-tactile material discrimination of fabrics. *J Vis* **16**, 1–15 (2016).

36. Vardar, Y., Wallraven, C. & Kuchenbecker, K. J. Fingertip Interaction Metrics Correlate with Visual and Haptic Perception of Real Surfaces. in *2019 IEEE World Haptics Conference, WHC 2019* (2019). doi:10.1109/WHC.2019.8816095.

37. Efron, B. Bootstrap Methods: Another Look at the Jackknife. *The Annals of Statistics* **7**, (1979).

38. Bergmann Tiest, W. M., Vrijling, A. C. L. & Kappers, A. M. L. Haptic discrimination and matching of viscosity. *IEEE Trans Haptics* (2013) doi:10.1109/ToH.2012.17.

39. Stilla, R. & Sathian, K. Selective visuo-haptic processing of shape and texture. *Hum Brain Mapp* (2008) doi:10.1002/hbm.20456.

40. van Assen, J. J. R., Barla, P. & Fleming, R. W. Visual Features in the Perception of Liquids. *Current Biology* (2018) doi:10.1016/j.cub.2017.12.037.

41. Schmidt, F., Paulun, V. C., van Assen, J. J. R. & Fleming, R. W. Inferring the stiffness of unfamiliar objects from optical, shape, and motion cues. *J Vis* (2017) doi:10.1167/17.3.18.

42. Bouman, K. L., Xiao, B., Battaglia, P. & Freeman, W. T. Estimating the material properties of fabric from video. in *Proceedings of the IEEE International Conference on Computer Vision* (2013). doi:10.1109/ICCV.2013.455.

43. Bi, W. & Xiao, B. Perceptual constancy of mechanical properties of cloth under variation of external forces. *Proceedings of the ACM Symposium on Applied Perception, SAP 2016* 19–23 (2016) doi:10.1145/2931002.2931016.

44. Cellini, C., Kaim, L. & Drewing, K. Visual and Haptic Integration in the Estimation of Softness of Deformable Objects. *Iperception* (2013) doi:10.1068/i0598.

45. Gregg, M. K. & Samuel, A. G. The importance of semantics in auditory representations. *Atten Percept Psychophys* (2009) doi:10.3758/APP.71.3.607.

46. Fleming, R. W. Material Perception. *Annu Rev Vis Sci* **3**, 365–388 (2017).

47. K. Rakhin, Onkar, P. Predicting Haptic Perception of Textile Texture and Analysis Between Smooth-Rough Preferences Through Images Predicting Haptic Perception of

Textile Texture and Analysis Between Smooth-Rough Preferences Through Images. (2018).

48. Ishihara, S. *Ishihara's Tests for Color Deficiency*. (Japan: Kanehara Trading Inc., 2004).

49. World Medical Association Declaration of Helsinki. *JAMA* **310**, 2191 (2013).

# Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementarymaterialMemorySoftness.pdf