

The look and feel of soft are similar across different softness dimensions

Müge Cavdan

Justus Liebig University, Department of Psychology,
Giessen, Germany



Knut Drewing

Justus Liebig University, Department of Psychology,
Giessen, Germany



Katja Doerschner

Justus Liebig University, Department of Psychology,
Giessen, Germany
Bilkent University, National Magnetic Resonance
Research Center, Ankara, Turkey



The softness of objects can be perceived through several senses. For instance, to judge the softness of a cat's fur, we do not only look at it, we often also run our fingers through its coat. Recently, we have shown that haptically perceived softness covaries with the compliance, viscosity, granularity, and furriness of materials (Dovencioglu, Üstün, Doerschner, & Drewing, 2020). However, it is unknown whether vision can provide similar information about the various aspects of perceived softness. Here, we investigated this question in an experiment with three conditions: in the haptic condition, blindfolded participants explored materials with their hands, in the static visual condition participants were presented with close-up photographs of the same materials, and in the dynamic visual condition participants watched videos of the hand-material interactions that were recorded in the haptic condition. After haptically or visually exploring the materials, participants rated them on various attributes. Our results show a high overall perceptual correspondence among the three experimental conditions. With a few exceptions, this correspondence tended to be strongest between haptic and dynamic visual conditions. These results are discussed with respect to information potentially available through the senses, or through prior experience, when judging the softness of materials.

Introduction

Objects in our world consists of single or composite materials. To be able to swiftly judge and recognize properties of materials is important, because perceived material qualities influence how we interact with an object. Humans have this ability and are able to make

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judgments about materials visually and haptically: we move a polished gemstone to visually judge its sparkle and rub a cloth to understand if it is soft enough to wear it. Recent research suggested that perceptions of different aspects of material qualities may be mediated by different senses (e.g. vision or touch, Adams, Kerrigan, & Graf, 2016; Sahli, Prot, Wang, Müser, Piovarči, Didyk, & Bennewitz, 2020). Often, however, also the same aspects of material qualities are judged through different senses: to judge the softness of our cat's fur, we do not only look at it, but we also run our fingers through its coat. In this example, the softness of the material can be assessed directly, by touching the cat (Lederman & Klatzky, 1987; Di Luca, 2014; Cavdan, Doerschner, & Drewing, 2021; Döveniçoglu et al., 2018), and also indirectly, by looking at it (Bergmann Tiest & Kappers, 2007; Giesel & Zaidi 2013; Schmidt, Paulun, van Assen, & Fleming, 2017). What is not known though is whether these two routes of processing might yield the same evaluations of softness.

Not just softness, but many material qualities are directly available through touch. Indeed, the topic has attracted attention in haptics community for quite a while (Lederman, 1974; Srinivasan, Whitehouse, & LaMotte, 1990; Srinivasan & LaMotte, 1995; for a review, see Bergmann Tiest, 2010) — increasingly so in the past few years (Cellini, Kaim, & Drewing, 2013; Drewing, Weyel, Celebi, & Kaya, 2018; Vardar, Wallraven & Kuchenbecker, 2019; Mezger & Drewing, 2019; Döveniçoglu et al., 2018; Cavdan et al., 2021; see Okamoto, Nagano, & Yamada, 2013 for a review). According to a meta-analysis by Okamoto et al. (2013) the tactual properties of materials can be categorized in five main sections, which are warmth (cold/warm), hardness (hard/soft), micro and macro roughness, and friction (moistness/dryness and stickiness/slipperiness).



Visually, only some material properties can be judged directly from images, such as surface gloss, transparency, or translucency. Thus, a large majority of research on the visual material perception has centered on those problems (e.g. see [Chadwick & Kentridge, 2015](#) for a review). Softness is related to the subjective impression of the compressibility and deformability characteristics of things and materials, which typically includes a relation to forces that can be directly sensed by touch, but not by vision. However, because of our lifelong experiences with materials (i.e. looking at them while we interact with them), we are also able to judge indirectly material properties from images (e.g. their rigidity, wobbliness, or stickiness; [Schmidt et al., 2017](#); [Alley, Schmid, & Doerschner, 2020](#)). Especially, when we watch objects move and materials deform, impressions of material qualities can be perceived quite vividly ([Sakano & Ando, 2010](#); [Doerschner, Fleming, Yilmaz, Schrater, Hartung, & Kersten, 2011](#); [Yilmaz & Doerschner, 2014](#); [Kawabe, Maruya, & Nishida, 2015a](#); [Kawabe, Maruya, Fleming, & Nishida, 2015b](#); [Bi & Xiao, 2016](#); [Marlow & Anderson, 2016](#); [Morgenstern & Kersten, 2017](#); [Schmidt et al., 2017](#); [Schmid & Doerschner, 2018](#); [van Assen, Barla, & Fleming, 2018](#); [Mao, Lagunas, Masia, & Gutierrez, 2019](#); [Alley et al., 2020](#)).

Interestingly, it is not just the deformation of a material that triggers a particular impression of the material quality but also watching the interaction with a material: when we actively explore materials in order to gain information about the objects, we adjust our hand and finger motions to the material properties (e.g. we tend to rub rough materials such as felt; [Dövcencioglu et al., 2018](#)) and to the information we want to gain (e.g. we apply pressure when we wish to find out about an object's deformability; [Lederman & Klatzky, 1987](#); [Lezkan, Metzger, & Drawing, 2018](#); [Cavdan, Doerschner, & Drawing, 2019](#); [Zoeller & Drawing, 2020](#); [Cavdan et al., 2021](#)). We know that observers can estimate the weight of lifted objects by just observing the lifting motion ([Bingham, 1987](#); [Hamilton, Wolpert, & Frith, 2004](#); [Hamilton, Joyce, Flanagan, Frith, & Wolpert, 2005](#); [Auvray, Hoellinger, Hanneton, & Roby-Brami, 2011](#); [Maguinness, Setti, Roudaia, & Kenny, 2013](#)), and more recent work has shown that humans can distinguish compliance by observing someone else's finger motions ([Cellini et al., 2013](#); [Drawing & Kruse, 2014](#)). Similarly, there has been evidence that visually observing exploratory hand motions of others can yield impressions of material qualities ([Yokosaka, Kuroki, Watanabe, & Nishida, 2018](#); [Wijntjes, Xiao, & Volcic, 2019](#)).

Do these sources of information (i.e. images, motion/deformations of the material, watching hand movements, and haptic exploration¹), provide rather complimentary or mostly redundant information? A high degree of redundancy might yield quite similar perceptual spaces when estimating material qualities on any of these sources of information (images,

haptic, image motion, etc.) in isolation. Whereas complimentary processing might yield somewhat different impressions of a material quality, say softness, when elicited by different sources of information. Although cue combination studies might provide some important insights into how information is integrated ([Wolfe, 1898](#); [Lederman, Thorne, & Jones, 1986](#); [Ellis & Lederman, 1999](#); [Cellini et al., 2013](#); [Lacey & Sathian, 2014](#); [Adams et al., 2016](#)), it is also of interest to understand how much the perception of a material quality from one source of information corresponds to the perception of the same material quality from another source of information. There are only a few studies that have investigated this. For example, [Vardar et al. \(2019\)](#) analyzed similarity ratings for a set of various materials (mounted flat on wood) based on visual or haptic comparisons and found the organization of the perceptual spaces suggests that vision and touch rely on congruent perceptual representations. [Baumgartner, Wiebel, and Gegenfurtner \(2013\)](#) used a more extended set of materials, but again limited to textures mounted flat on wood, and assessed ratings of material qualities for visually and haptically presented materials. They conclude that material representations might overall be similar in visual and haptic domains, however, how well ratings in visual and haptic domains agree, appears to be depended on the attribute being rated ([Baumgartner et al. 2013](#), their figure 7). [Xiao, Bi, Jian, Wei, and Adelson \(2016\)](#) investigated the perception of fabrics and found that visuo-haptic matching improves when visually presented fabrics were draped instead of mounted flat, and [Wijntjes et al. \(2019\)](#) showed that movies can reveal more about how fabrics feel than can still images.

What might complicate comparisons of perceptual experience across the senses is that many perceptual attributes are not very well defined. For example, we have recently shown that, perceived softness, which, in haptic research, has traditionally been equated with the compliance of a material ([Kaim & Drawing, 2011](#); [Cellini et al., 2013](#); [Di Luca, 2014](#); [Punpongsonon, Iwai, & Sato, 2015](#); [Kitada, Doizaki, Kwon, Tanigawa, Nakagawa, Kochiyama, Kajimoto, Sakamoto, & Sadato, 2019](#); [Zoeller, Lezkan, Paulun, Fleming, & Drawing, 2019](#)) is in fact a multidimensional construct, that consists of several qualities, such as surface softness, granularity, and viscosity ([Cavdan et al., 2019](#); [Dövcencioglu et al., 2018](#); [Cavdan et al., 2021](#)). This makes intuitively sense: the softness of sand on a beach is different than the softness of a rabbit's fur, or the softness of an avocado, and we even found that this dimensionality is reflected in the way we explore the material and what property we judge ([Cavdan et al., 2019](#); [Dövcencioglu et al., 2018](#); [Cavdan et al., 2021](#)). Thus, if one were to compare haptic and visual perception of softness, one would have to be careful to compare all of the underlying dimensions of this perceptual attribute. This is the goal of this study.

Specifically, we seek to understand to what extent the dimensions of perceived softness, that we found in previous haptic experiments, are also present in vision. To do so we conducted an experiment with two visual conditions, including a wide range of materials. In one condition, we present movies showing interactions with materials while doing a rating task. This provided observers with the maximum amount of visual information possible, not just showing how materials deform but also typical interactions while rating material qualities (dynamic condition). In a second condition, the visual information was reduced, showing only still photographs of the same set of materials (static visual condition). We compare results of the visual experiment to data from a corresponding haptic study by our group (Cavdan et al., 2021). We hypothesize that the correlation between the perceptual softness spaces yielded by the two visual conditions should be stronger than the correlation between visual and haptic perceptual spaces, because ratings in the former are based on the same type of indirect information (i.e. visual; Paulun, Schmidt, van Assen, & Fleming, 2017; van Assen et al., 2018; Wijntjes et al., 2019). Given previous results by (Wijntjes et al., 2019), we further hypothesize that the correlation between the perceptual spaces yielded by the dynamic visual condition and the haptic experiment should be stronger than the one between the static visual condition and the haptic experiment.

General methods

Overview

We investigate to what extent the dimensions of perceived softness that we found in previous haptic experiments are also present in visual representation of material qualities. To do this we selected a set of everyday materials that we found to be representative for the various perceptual dimensions of softness in haptic experiments (Cavdan et al., 2019; Dövcencioglu et al., 2018; Cavdan et al., 2021). Similarly, we used rating attributes that we found to be strongly associated with the respective perceptual dimensions of softness. Previously recorded hand movements during haptic exploration of these materials were used for the dynamic visual condition, and still photographs of images of the materials in the static visual condition. Participants rated all stimuli on all attributes. A Principal Component Analysis (PCA) was used to determine the perceived softness dimensions for static and dynamic visual conditions. We then formally compare the resulting visual and haptic perceptual softness spaces using Procrustes and correlation analyses. Along with information pertaining to the visual experiments, we will highlight the relevant methodological and analysis aspects of the previous

haptic study (data from the haptic condition has been reported in part in Cavdan et al., 2021, also see this paper for more methodological details), which we refer to as haptic condition in the remainder of this paper.

Participants

Ninety students participated in the experiments: static visual condition: 20 women and 10 men; mean age 23.4 years, range = 20 to 31 years; dynamic visual condition: 21 women; age range = 20 to 33 years; mean age = 25.1; haptic condition = 21 women and 9 men; mean age = 23.6 years; range = 18 to 38 years. All of them were right-handed according to self-report, spoke German at a native speaker level, and were naïve to the purpose of the experiment. Participants in both visual conditions had normal or corrected-to normal visual acuity and normal color vision (Ishihara, 2004). Participants in the haptic condition had no sensory, motor, or cutaneous impairments and had a two-point discrimination threshold, at the index finger of the right (dominant) hand, of 3 mm or better. Participants provided written informed consent prior to the experiments. All the experiments were approved by the local ethics committee of Giessen University, LEK FB 06, and were conducted in accordance with the Declaration of Helsinki.

Stimuli

Material items were the same as in our previous haptic study (Cavdan et al., 2021), and included those that had resulted in extreme positive or negative values on four softness-related (Deformability, Fluidity, Hairiness, and Granularity) and one control dimensions (Roughness), but included also those that did not show either extreme positive values in any perceptual dimension or that showed extreme values in more than one dimension (see Figure 1, and Dövcencioglu et al., 2018, Cavdan et al., 2021). Roughness is a well-established material dimension in haptics (Bergmann Tiest & Kappers, 2007; Okamoto et al., 2013). Therefore, in order to test the validity of our paradigm (in Cavdan et al., 2021) we included adjectives that are known to load high on this dimension as well as materials that are known to be perceived as haptically rough. However, it is quite possible that visual information of haptically rough materials might not provide adequate information for judging the roughness of more fine-grained textures (Heller, 1989), which might lead to differences in what the roughness dimension might look like (e.g. its patterns of adjective loadings) in the visual experiments.

Still images

To generate still photographs of all 19 materials we placed individual materials on a green cloth (see

Static	Deformability	Fluidity	Surface softness	Granularity	Roughness	Dynamic	Hand Movement	Static	Deformability	Fluidity	Surface softness	Granularity	Roughness	Dynamic	Hand Movement
	-						rotate						+		rub
	-						pressure & rub			-			-		rub
	-						pressure & rub								rub
		+					pull & rub				+		+		rub
		+					pull & rub		+				+		rub
			+				rub								run through
			+				rub			+	-		+		run through & rotate
				+			run through & rotate				+		+		pressure & rub
				+			run through & rotate		+		+				rub
					+		rub								

Figure 1. Images used as static visual stimuli (column 1), associated dimensions of the materials (negative loadings (-), positive loadings (+)), associated hand movements from Cavdan et al. 2021 (column 7), and example frames from dynamic visual stimuli (column 8). The names of the materials from top to bottom are pebbles, stress balls, play dough, hair gel, hand cream, fur, velvet, sand, salt, sandpaper, felt, aluminum foil, paper balls, wool, linen, lentils, cranberries, sponge, and cotton balls.

Figure 1). Where possible we added traces of a manual manipulation (e.g. playdough with indentation of fingers and sand with some run-through marks) in order to increase the available shape cues to the respective material properties. Photographs were taken close-up using a Sony Digital 4K Video Camera Recorder, which took 60-bit images at a spatial resolution of 3840 × 2160 pixels (white balance shift disabled), and with materials illuminated by two 1320 lumen light bulbs placed left and right to the material. This setup yielded a natural look of the materials and minimized harsh shadows. Postprocessing of images centering of the material and cropping to a size of 2049 × 1464 pixels (The GIMP Development Team, 2019).

Dynamic stimuli

For the dynamic visual condition, we used some of the previously recorded hand movements in the haptic experiments. We selected movies as follows:

First, we determined either the one or two most frequently used typical exploratory hand movements

per material using the taxonomy of Cavdan et al. (2021). For example, the most frequently used hand movements for salt were “run through” and “rotate” (run through: “Picking up some parts/portion of the material and letting them trickle through the fingers,” rotate: “Lifting parts of the material to move and turn its boundaries typically inside the finger(tip)s”; Cavdan, et al., 2021, page 2). Definitions of all exploratory hand movements can be found in Supplementary Methods S1. Most frequently associated hand movements for each material can be found in Figure 1, column 8.

Second, from the movie material collected during the haptic experiment, we selected videos of different participants that performed these typical hand movements. For each of the 19 materials, we randomly choose videos of 3 different participants performing the same hand motion, in order to avoid perceptual biases due to a given participant’s potentially unique exploration style. Videos were clipped to 6 seconds (180 frames) with a resolution of 1012 × 1080 pixels. This resulted in 3 matched sets of 19 clips each (one clip per material). Figure 1,

column 7 shows sample snapshots from the movies used in the dynamic visual condition.

Adjectives

Stimuli were rated on the same 15 sensory adjectives that we used in the previous haptic experiment (Cavdan et al., 2021). These adjectives had been selected based on their association (positive or negative) with the above-described softness dimensions or the control dimension (Dövcencioglu et al., 2018). These were *soft*, *elastic*, *hard*, *inflexible*, *moist*, *wobbly*, *sticky*, *sandy*, *powdery*, *granular*, *velvety*, *fluffy*, *hairy*, *rough*, and *smooth* (see Cavdan et al., 2021 for more details of the selection criteria for adjectives).

Apparatus

In the static visual condition, stimuli were displayed on a Samsung UHD (U32D970Q) 32 inch Professional LED monitor (resolution: 3840×2160 , refresh rate: 55 Hz). Participants were seated at a distance of about 70 cm from the screen, thus the stimulus size in visual angle on the screen was about 24 degrees in width and about 20 degrees in height.

In the dynamic visual information condition, stimuli were presented on a DELL UltraSharp monitor (resolution: 2560×1440 , refresh rate: 56 Hz). Participants were seated at a distance of about 70 cm from the screen, thus the stimulus size in visual angle on the screen was about 15 degrees in width and about 15 degrees in height. Videos were played at a rate of 30 frames per second.

The experiment was programmed in MATLAB 2017a (2007; MathWorks Inc., New York, NY, USA) using Psychtoolbox routines (Brainard, 1997; Kleiner, Brainard, & Pelli, 2007). Responses were collected with a keypad.

In the previous haptic experiment (Cavdan et al., 2021), we used a curtain to hide the materials from the participant's view and active noise cancelling headphones to eliminate any contact sounds. Material stimuli were presented on a plastic plate and the participant's arm was placed on a wrist rest that allowed to explore the materials comfortably from a defined position. Hand movements of the participants were recorded and used in the dynamic visual condition, as described in the sections above (for more details of this study please see Cavdan et al., 2021).

Design and procedure

Static condition

On each trial, participants first saw the to-be-rated adjective. After pressing the space button, an image of a material appeared and stayed for 2 seconds at the center of the screen. After the image disappeared, observers gave their ratings using the keypad. The task was to indicate how much a given adjective applies to the just seen material on a 5-point Likert scale item ranging from 1 (adjective not applicable) to 5 (adjective strongly applies). Participants completed 285 trials (19 materials \times 15 adjectives) in about 1 hour. The order of material-adjective pairs was randomized, every participant saw every material-adjective pair only once (Figure 2).

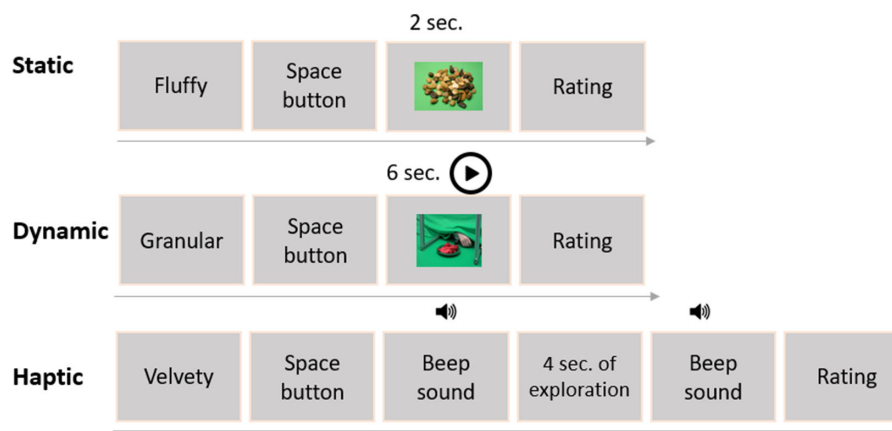


Figure 2. Time course of a trial across conditions in the experiment. First, in all conditions, the adjective to be rated appeared on the screen. After pressing the space button an image was presented on the screen for 2 seconds in static visual and a video presented on the screen for 6 seconds in the dynamic visual condition. In the haptic condition a sound (beep) signaled the start for 4 seconds of exploration, and a second beep signaled the end of the trial. Subsequently, in all conditions, participants indicated how much the given adjective applied to the material on a 5-point Likert scale.

Dynamic condition

The procedure in the dynamic visual condition was similar to the static visual condition except that, instead of a static image, observers now saw a 6 second movie clip showing the exploration of a material (see Figure 2). Observers had to rate all three sets of dynamic visual stimuli, each set on a separate day. Each session (19 movie clips \times 15 adjectives) took about 1 hour.

Haptic condition

A typical trial in the haptic condition is shown in Figure 2. In summary, participants first saw the to-be-rated adjective, then pressed the space button to start exploration. Materials were explored for 4 seconds with the right hand. After the exploration, participants removed their hands from the material and rated the material according to the adjective by using keypad using with their left hand. The order of materials and adjectives was randomized, and the experiment took about 1.5 hours.

Analysis

The goal of this study was to determine the dimensionality of visually perceived softness and to compare it to the dimensionality of the haptic perceptual space.

As a first step, we assessed interobserver consistency in the ratings, and checked whether this was approximately in the same range as that obtained for haptic data. Because we acquired three data points for each material-adjective combination in the dynamic visual condition (i.e. 3 videos for each material-exploration stimulus) we used the average of these three scores in the consistency and all subsequent analyses. Next, we performed separate PCAs for static and dynamic visual conditions based on average observer data from material-adjective pairs (19 materials \times 15 adjectives = 285 data points). We also extracted Bartlett scores which essentially provide an estimate of how strongly each stimulus (material) scores on each extracted dimension. The score is calculated from the adjective ratings for that material weighted by the adjective loadings for the respective dimension. Comparing the resulting factor structure and loadings would allow for a first assessment of similarities between visual softness dimensions, and for comparing these to the previously determined haptic perceptual space. To formally assess the degree of similarity we conducted a Procrustes analysis on the Bartlett score values of each material across conditions. Should the visual perceptual spaces turn out to be overall similar

to each other and the haptic space, we would follow this analysis with a combined PCA on ratings of the visual conditions and the previous haptic experiment. This would allow for a more fine-grained assessment of the structural similarities of static visual, dynamic visual, and haptic perceptual softness spaces (e.g. by inspecting the correlations of the respective Bartlett scores between spaces), for all softness dimensions; (e.g. static visual dimension 1 versus haptic dimension 1: static visual dimension 1 versus haptic dimension 2, etc.).

Last, we directly investigated whether there were rating differences between the two visual conditions and the haptic condition. To this end, we first calculated mean ratings across participants for each material-adjective pair for the two visual conditions and the haptic experiment, and then computed the distances between these means (3 distances: static-dynamic, static-haptic, dynamic-haptic, for each of the 285 material-adjective pairs). Then we resampled these data using Monte Carlo methods (Efron, 1979), creating a random sample of 10,000 rating distances. We determined the 95% percentile of this distribution and report the conditions in which rating difference exceeded this cutoff value. Assuming that the distribution of distances does not depend on the conditions that are being compared (H versus D versus S), makes the following prediction: in the extreme 5%, the case count (n) of distances should be the same when considering haptic and static visual ratings (HS), haptic and dynamic visual ratings (HD), and visual static and dynamic ratings (SD), such that n_{HS} (i.e. number of extreme haptic-static distances) = n_{SD} (i.e. number of static-dynamic distances) = n_{HD} (i.e. number of haptic-dynamic distances). However, if our three hypotheses are true, then we would expect this to be reflected in the case count of each comparison (i.e. $n_{HS} > n_{SD}$, $n_{HD} > n_{SD}$, $n_{HS} > n_{HD}$).

Using a binomial distribution, we test, for each of the three hypotheses, whether the number of extreme cases is equal.

Results

Interobserver consistency

Overall, all interindividual correlations between participants' ratings in static and dynamic visual conditions were significant ($p < 0.01$), and ranged between 0.41 to 0.81 and 0.41 to 0.95, respectively (also see Supplementary Figures S1, S2). These values were comparable to previously reported results in the haptic condition (0.45 - 0.86, Cavdan et al., 2021) and suggest that participants' interpretation of the perceptual meaning of adjectives tended to agree. All subsequent

Adjective	Static			Dynamic				Haptic				
	I. Surface softness/Deformability	II. Granularity	III. Viscosity	I. Surface softness	II. Granularity	III. Viscosity	IV. Deformability	I. Surface softness	II. Granularity	III. Viscosity	IV. Deformability	V. Roughness
Fluffy	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	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	0.84	-0.10	-0.41	0.83	-0.10	-0.27	-0.15	1.07	-0.39	-0.25	0.06	0.48
Velvety	0.74	-0.09	-0.24	0.69	0.04	-0.05	-0.06	0.81	0.01	-0.18	-0.32	-0.15
Elastic	0.62	-0.33	0.39	0.11	-0.19	0.17	-0.75	0.10	-0.32	0.28	0.80	0.09
Hard	-0.91	0.15	-0.38	-0.52	0.05	-0.42	0.63	-0.61	0.17	-0.41	-0.91	0.09
Inflexible	-0.72	0.33	-0.21	-0.30	0.27	0.00	0.75	-0.24	0.43	0.07	-0.84	-0.04
Sandy	-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	-0.55	1.03	-0.20	-0.29	0.90	-0.18	0.55	-0.41	1.10	-0.03	0.68	0.22
Powdery	-0.20	0.94	-0.07	-0.05	0.92	-0.02	0.28	-0.06	0.97	-0.05	0.17	0.10
Rough	-0.41	0.76	-0.39	-0.30	0.54	-0.57	-0.02	-0.39	0.38	-0.33	0.14	0.70
Smooth	-0.38	-0.61	0.09	-0.13	-0.50	0.23	0.30	-0.27	-0.20	0.11	0.12	-0.95
Sticky	-0.12	-0.13	0.98	-0.18	-0.03	0.88	-0.12	-0.26	0.04	1.11	-0.16	-0.08
Moist	-0.11	-0.16	0.91	-0.15	-0.19	0.99	-0.02	-0.12	0.03	1.14	0.05	-0.25
Wobbly	0.18	-0.27	0.78	-0.13	-0.16	0.70	-0.42	0.03	-0.22	0.96	-0.40	-0.04

Table 1. Adjective loadings after rotation for static and dynamic visual data, as well as for the previous haptic experiment. Each factor labeled based on the adjectives load high (>40% of mean variance per adjective explained: 0.68 static visual, 0.62 dynamic visual, and 0.74 for haptic sequentially) and load higher on a specific factor than the others. Bold if loading both maximal for adjective and >40% of mean variance per adjective explained, italic if loading only maximal for adjective. Darker colors show positive loadings and lighter colors indicate negative loadings.

analyses were done on ratings that were averaged across participants.

PCA for static and dynamic visual rating data

Because participants showed high consistency in their rating data, we performed next covariance PCAs for static and dynamic visual conditions. The Keyser-Meyer-Olkin (KMO) criterion was 0.4, and 0.5 for the static and dynamic visual conditions, respectively, which are borderline values. However,

Bartlett's test of sphericity was significant for both conditions ($p < 0.01$): $\chi^2(105) = 370.32$, $\chi^2(105) = 360.03$, suggesting that the observed correlations between adjectives were meaningful. Components which had eigenvalues bigger than one were extracted and rotated using the varimax method.

In the static visual condition, we extracted three components explaining 83.9% of the total variance (see Table 1). The first component, which we termed surface softness/deformability, accounted for 38.2% of the variance with significant loadings of the adjectives soft, elastic, hard, velvety, hairy, fluffy, and inflexible;

the second component, which we named granularity, accounted for 25.8% of the variance with significant loadings of the adjectives granular, sandy, powdery, rough, and smooth; the third component, termed viscosity, accounted for 19.9% of the variance with significant loadings of the adjectives wobbly, sticky, and moist.

In the dynamic visual condition, we extracted 4 components explaining 89.2%. Whereas three of the components were rather similar in their structure to the static visual condition (surface softness [25.2%, soft, velvety, hairy, and fluffy], granularity [23.7%, granular, sandy, powdery, and smooth], viscosity [21.8%, wobbly, sticky, moist, and rough]), a fourth component appeared to be exclusively related to the deformability of the material. This fourth component accounted for 18.5% of the variance with significant loadings of the adjectives elastic, hard, and inflexible.

In comparison, in our previously reported haptic condition, we had extracted four components related to softness (surface softness [25.9%, soft, velvety, hairy, and fluffy], viscosity [20.6%, wobbly, sticky, and moist], granularity [20.6%, granular, sandy, and powdery], deformability [17.8%, elastic, hard, and inflexible]) as well as one component related to the roughness of the material (roughness [9.5%, rough and smooth]).

Although there are some differences in the number of extracted components between the two visual conditions and the haptic one, it becomes also apparent that there are some structural similarities in the extracted components between the visual and haptic conditions. In particular, inspecting Table 1, in all three conditions, the components of surface softness, granularity, and viscosity account for most of the variance in the ratings, with nearly the same patterns of adjective loadings. To formally assess the degree of similarity we conducted a Procrustes analysis on the Bartlett score values of each material across these three components (surface softness, granularity, and viscosity) among static visual, dynamic visual, and haptic conditions. This analysis aims to map two multidimensional representations onto each other using linear transformations (reflection, translation, and orthogonal rotation). From this analysis we obtained an index of the error (mean squared error across point pairs) that remains after applying this transform, with lower values indicating better fits. Comparing the mapping of perceptual spaces among the three conditions we obtained values of 0.19 (static visual versus dynamic visual), 0.20 (static visual versus haptic), and 0.25 (dynamic visual versus haptic). These values were all comparably low (also see Supplementary Figure S4), indicating a rather high similarity among the three perceptual spaces, spanned by the dimensions of surface softness, granularity, viscosity (also see Supplementary Figure S3). Thus, we determined that the structural similarity was sufficient to proceed with

a combined PCA for static visual, dynamic visual, and haptic rating data, which would allow us to make more fine-grained comparisons among the static visual, dynamic visual, and haptic spaces of perceived softness.

Combined PCA for static visual, dynamic visual, and haptic rating data

A KMO value of 0.68 and a statistically significant Bartlett's test of sphericity ($\chi^2(105) = 1225.62, p < 0.01$) suggest that a PCA was indeed appropriate for the combined dataset (Francis & Field, 2011). The combined PCA yielded 4 components explaining 88.6% of the total variance. The adjectives soft, fluffy, hard, velvety, and hairy loaded high on the first component, which explained 30.04% of the total variance, and given its loading patterns we named it surface softness. The adjectives sandy, granular, powdery, inflexible, and elastic loaded high on the second component, which explained 27.37% of the total variance. We named this second component granularity. The adjectives sticky, moist, and wobbly loaded high on the third component, which appeared to be related to the viscosity of materials, accounting for 22.30% of the variance. The adjectives rough and smooth loaded high on the fourth component, which explained 8.89% of the variance. Because of these loading patterns we called it roughness. Table 2 shows the adjective loadings for each of the four components in this combined PCA analysis, and Figure 3 shows the corresponding Bartlett scores of all materials, sorted according to their sign and magnitude in the haptic condition (i.e. in order to allow for a better comparison across the three conditions, we kept the ordering of materials in the two visual conditions the same as in the haptic one).

Assessing similarities between the static visual, dynamic visual, and haptic spaces of perceived softness

In order to determine the similarities between the static visual, dynamic visual, and haptic perceptual spaces of perceived softness, we compared the correlation scores of the Bartlett scores of the three softness dimensions (surface softness, granularity, and viscosity) and roughness across all materials (see Figure 3). The correlations among perceptual spaces (i.e. dynamic-haptic, static-haptic, and dynamic-static) were significantly different from 0 (Bonferroni corrected for 3 tests, $\alpha = 0.05/3 = 0.017$). Figure 4 shows that, overall, the correlations were high among the three perceptual spaces: static and dynamic ($r = 0.964, p <$

Adjective (English /German)	I. Surface Softness	II. Granularity	III. Viscosity	IV. Roughness
Explained variance	30.04%	27.37%	22.30%	8.89%
Fluffy / flauschig	1.23	-0.25	-0.34	-0.10
Soft / weich	1.01	-0.30	0.44	-0.16
Hairy / haarig	0.85	-0.21	-0.37	-0.16
Velvety / samtig	0.80	-0.07	-0.10	0.05
Hard / hart	-0.71	0.37	-0.52	0.31
Granular / körnig	-0.39	1.13	-0.19	-0.06
Sandy / sandig	-0.16	1.06	-0.13	-0.28
Powdery / pulverig	-0.39	0.93	-0.03	-0.19
Inflexible / unbiegsam	-0.42	0.64	-0.17	0.44
Elastic / elastisch	0.31	-0.52	0.41	-0.37
Sticky / klebrig	-0.18	-0.03	0.97	0.08
Moist / feucht	-0.14	-0.05	0.96	0.26
Wobbly / wabbelig	0.03	-0.29	0.85	-0.05
Smooth / glatt	-0.19	-0.25	0.17	0.74
Rough / rau	-0.39	0.47	-0.44	-0.54

Table 2. Rotated Adjective loadings obtained from the combined PCA analysis (static visual, dynamic visual and haptic conditions). Color-codes, font styles, and criterion for significance ($>40\%$ of mean variance = 0.67) are as in Table 1.

0.001), dynamic and haptic ($r = 0.96$, $p < 0.001$), and static and haptic spaces ($r = 0.93$, $p < 0.001$).

We next tested our three hypotheses, namely that the correlation between the two visual conditions should be significantly stronger than any other correlation and that the correlation between the dynamic visual condition and the haptic experiment should be stronger than the correlation between static visual condition and haptic experiment. These are planned comparisons, and we therefore did not correct for multiple comparisons. We computed Fisher r to z transformations for analyzing the statistical significance of the difference between two correlation coefficients (Fisher, 1915; Eid, Gollwitzer, & Schmitt, 2011). Figure 4 illustrates that the correlation between dynamic visual and static visual

spaces was indeed significantly larger than that between static visual and haptic spaces ($p = 0.02$, one-tailed), however, it was not significantly larger than the dynamic-haptic correlation ($p = 0.37$). Pertaining to the third hypothesis we found indeed that the correlation between the dynamic-haptic spaces was larger than that between static visual and haptic spaces ($p = 0.04$, one-tailed).

It is further possible that the strength of the correspondence might vary between the respective softness dimensions (i.e. for surface softness, granularity, viscosity, or roughness). To investigate this possibility, we computed the correlations of Bartlett scores also at the dimensional level (note that significance level was determined after correcting

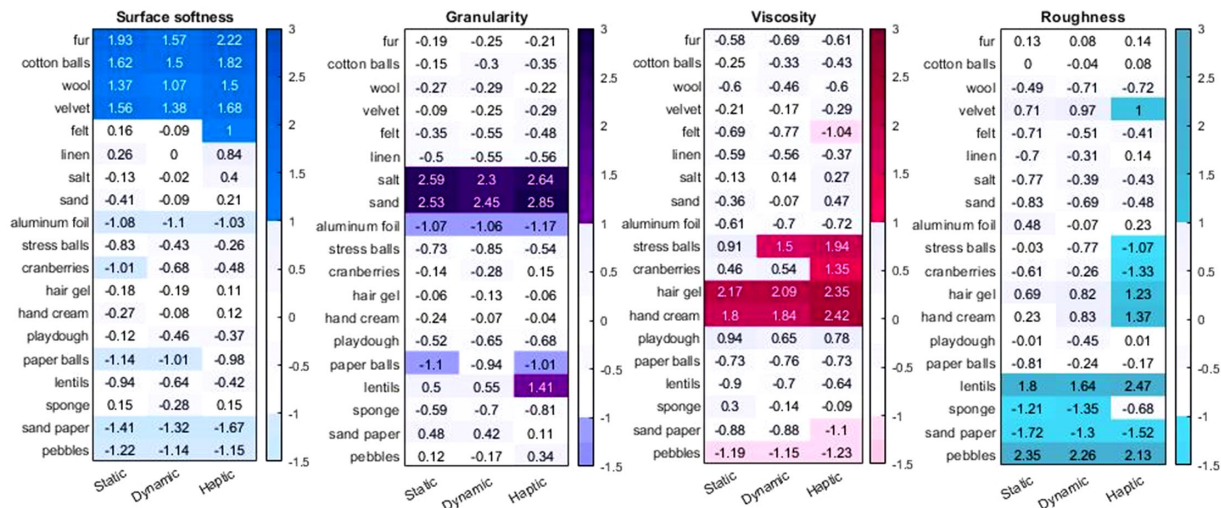


Figure 3. Rotated component scores (Bartlett scores) of materials — in each perceptual softness dimension: surface softness, granularity, viscosity, and roughness dimensions — for haptic, dynamic visual, and static visual conditions, respectively. Darker, saturated colors indicate positive loadings and desaturated, lighter colors represent negative loadings. Light violet and white areas indicate that loadings were larger than -1 standard deviation, or smaller than 1 standard deviation.

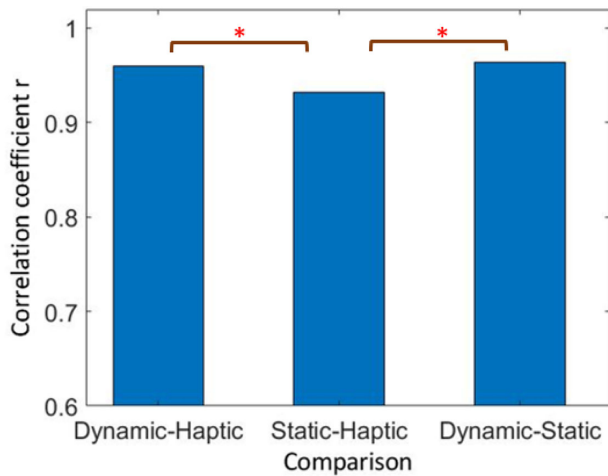


Figure 4. Comparisons of correlation coefficient r across dynamic visual information-haptic, static visual information-haptic, and dynamic visual information-static visual information conditions. Asterisks represent significance levels (*: $p < 0.05$).

for 48 tests: $\alpha = 0.05/48 = 0.001$; Curtin & Schulz, 1998). As expected, the correlations across conditions (static visual, dynamic visual, and haptic) within the respective dimensions were very high and statistically significant (Figure 5, dark blue colors, all $p < 0.001$), and correlations across the respective dimensions were low and not significantly different from 0 (light blue colors).

We next also put here our three hypotheses to the test. Regarding the first two hypotheses, which state that the correlation between the two visual conditions should be strongest, we find, in line with our prediction, that for all tested dimensions (surface softness, granularity, viscosity, and roughness) the correlation between static-dynamic spaces was higher than that between static-haptic spaces ($r_{softness} = 0.975$ vs. 0.961 , $p = 0.26$, $r_{granularity} = 0.993$ vs. 0.969 , $p = 0.02$, $r_{viscosity} = 0.973$ vs. 0.942 , $p = 0.13$, $r_{roughness} = 0.927$ vs. 0.877 , $p = 0.22$, all one-tailed). However, the correlation between static-dynamic spaces was higher than that between dynamic-haptic spaces only for two of the dimensions: softness and granularity ($r_{softness} = 0.975$ vs. 0.968 , $p = 0.36$, $r_{granularity} = 0.993$ vs. 0.973 , $p = 0.03$, $r_{viscosity} = 0.973$ vs. 0.982 , $p = 0.28$, $r_{roughness} = 0.927$ vs. 0.927 , $p = 0.05$, all one-tailed). Note, that none of the individual comparisons reached statistical significance after correcting for multiple (4) comparisons ($p_{corrected} = 0.05/4 = 0.0125$). Our third hypothesis was that the correlation between the dynamic visual and the haptic conditions would be stronger than the correlation between the static visual and haptic conditions. Whereas, again, we numerically observed this trend for all four dimensions ($r_{softness} = 0.986$ vs. 0.961 , $r_{granularity} = 0.973$ vs. 0.969 , $p = 0.42$, $r_{viscosity} = 0.982$ vs. 0.942 , $p = 0.046$, $r_{roughness} = 0.927$ vs. 0.877 , $p = 0.22$, all one-tailed), none of the differences were statistically significant ($p_{corrected} = 0.05/4 = 0.0125$).

These analyses suggest that despite an overall good agreement among static visual, dynamic visual, and haptic perceptual softness spaces, there are also some

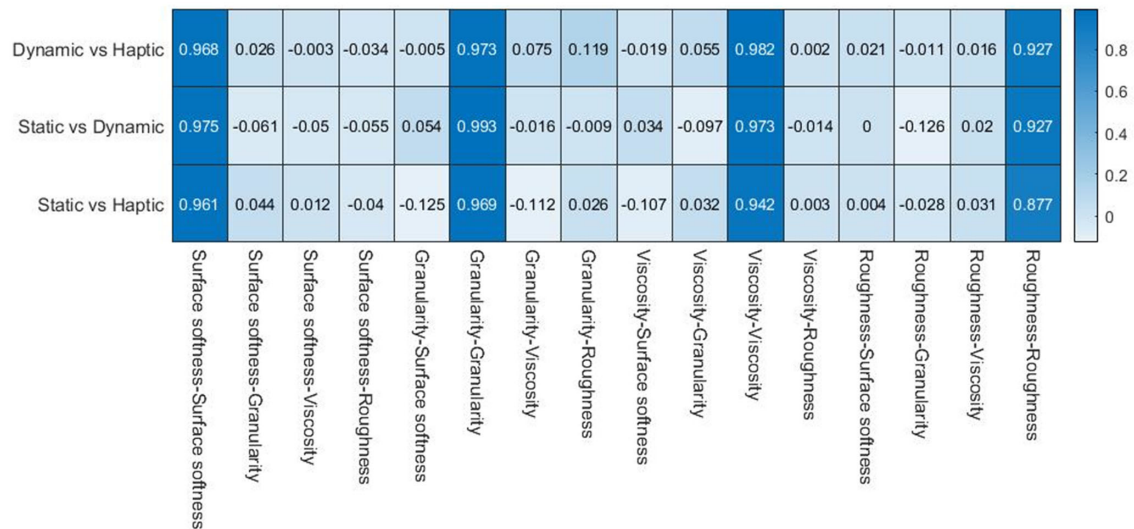


Figure 5. Correlations between Bartlett scores across materials for either pair of component scores from the haptic, the dynamic, and the static visual conditions. Darker colors (blue) show higher while lighter colors (white) show lower correlations.

interesting trends that suggest that the softness of some materials is represented slightly differently in each of these spaces. In the next analysis, we will follow-up on this observation and analyze the ratings directly in order to understand for what material-adjective pairs the ratings of participants differ the most.

Rating differences among static visual, dynamic visual, and haptic conditions

Overall, only 35 out of the 855 (285 × 3) rating differences exceeded the determined cutoff value. If our three hypotheses were true, then we would expect the case count in these extreme 5% to be different in each comparison such that nHS > nSD, nHD > nSD, nHS > nHD. We tested this with a binomial test, where we determined, for each of the three hypotheses, whether the number of extreme cases is equal ($p = 0.05$). In line with our expectation, we find that haptic-static extremes ($N = 19$) were significantly more cases than static-dynamic ($N = 2$; $p < 0.01$), that haptic-dynamic extremes ($N = 14$) were significantly more than static-dynamic ($N = 2$; $p < 0.01$), and the number of haptic-dynamic haptic-static extremes ($N = 19$ and $N = 14$) were about the same ($p = 0.24$). Consequently, we rejected the idea that, overall, the extreme rating differences came from a random distribution, and proceeded with the inspection of patterns in the cases where we found extreme differences between haptic and one or both visual conditions.

Three groups of difference patterns can be distinguished. In one group, there were extreme differences between haptic and both visual conditions. In Figure 6, we show these differences in a bar plot. The x-axis shows the corresponding adjective and material that elicited these rating difference. To appreciate what a specific bar height means, remember that ratings in all experiments varied between 1 (does not apply at all) and 5 (strongly applies). A positive difference implies that participants thought that a particular adjective applied more to the material in question (e.g. that pebbles, lentils, or cranberries felt more granular than they looked in either the dynamic visual or static visual conditions, that linen felt softer than it looked, or that fur feels more velvety than it looks). For this group, it appears that haptic information conveys information about material properties that is distinct from that conveyed by visual information (consistent with our first and second hypotheses above).

In a second group, there were extreme differences between haptic and static visual conditions but not between haptic and dynamic visual ones. For example, the softness of sand, salt, and cranberries was judged differently in haptic and static visual conditions, as was the hardness of stress balls (Figure 7). Here, it appears that the dynamic visual condition conveyed similar information as the haptic condition (as we also expected in our third hypothesis above).

Last, the third group of differences was the most surprising, containing cases with extreme differences between haptic and dynamic visual conditions only (Figure 8). This goes directly against our third hypothesis (nHS > nHD), which proposed that dynamic visual and haptic conditions should yield

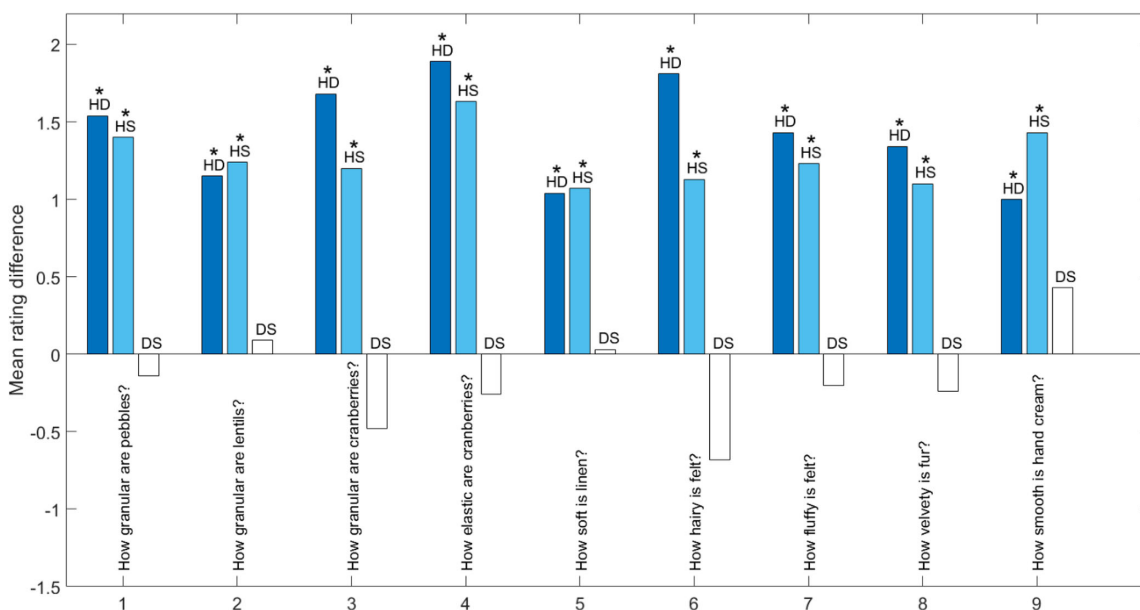


Figure 6. **Extreme distances in haptic-static and haptic-dynamic.** Mean rating differences between haptic-dynamic and haptic-static for specific material-adjective pairs. HD refers to the differences in rating between haptic and dynamic visual conditions (dark blue) and HS to the differences in rating between haptic and static visual conditions (light blue). * Show the mean differences larger than 95% percentile cut off value (see Methods).

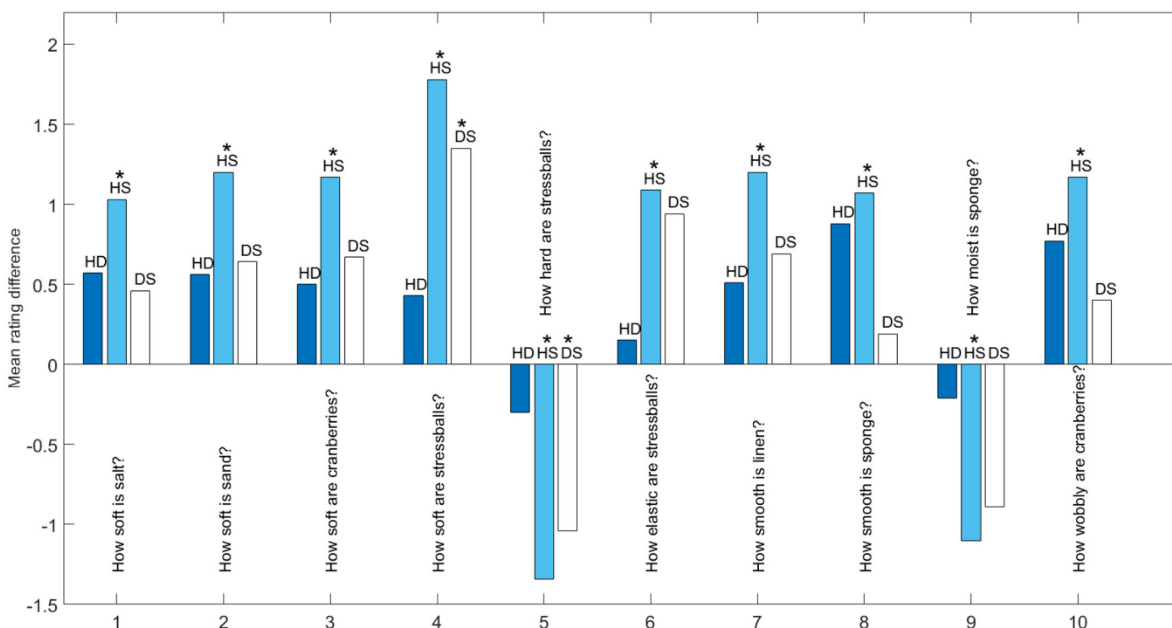


Figure 7. **Extreme distances in haptic-static.** Mean rating differences between haptic-dynamic and haptic-static for specific material-adjective pairs. Symbols and colors as in Figure 6.

more similar outcomes. Instead, for judgments of “how smooth lentils are” or “how velvety linen is,” dynamic visual information appears to bias

the participants away from the material properties perceived by inspecting a static image or by feeling the materials.

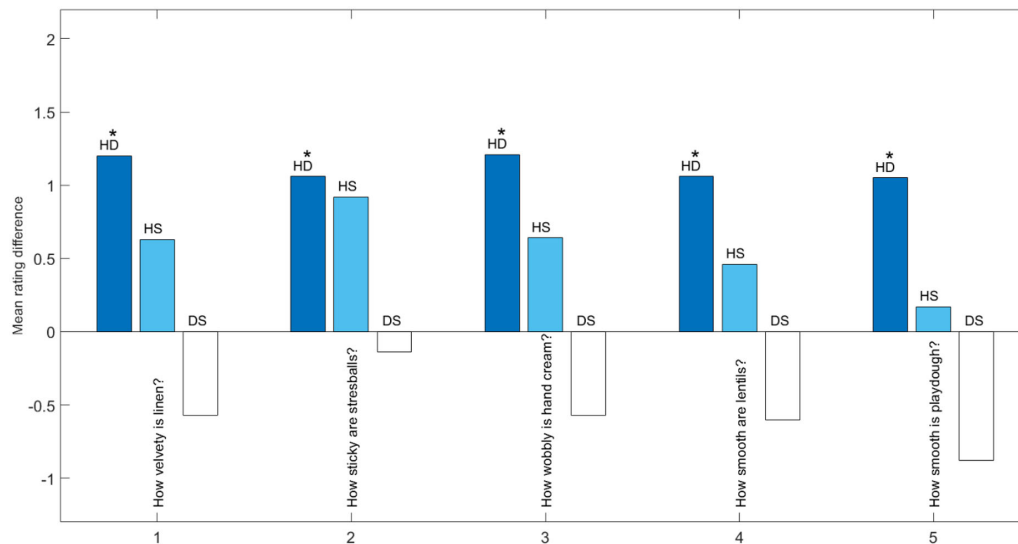


Figure 8. **Extreme distances in haptic-dynamic.** Mean rating differences between haptic-dynamic and haptic-static for specific material-adjective pairs. Symbols and colors as in Figures 6 and 7.

Discussion

Softness is a prominent object property that renders it — depending on our intentions — useful (soft pillows) or useless (soft tables), appealing (soft fur) or repulsive (soft apples) to us. Whereas we think of softness as primarily a mechanical property that can be perceived through touch (Lederman & Klatzky, 1987; Cellini et al., 2013; Okamoto et al., 2013; Di Luca, 2014; Cavdan et al., 2019; Higashi, Okamoto, Yamada, Nagano, & Konyo, 2019; Kitada et al., 2019; Dövecioglu et al., 2018; Xu, He, Hauser, & Gerling, 2020) softness can also be judged visually (Drawing, Ramisch, & Bayer, 2009; Baumgartner et al., 2013; Bouman, Xiao, Battaglia, & Freeman, 2013; Giesel & Zaidi, 2013; Bi & Xiao, 2016; Bi, Jin, Nienborg, & Xiao, 2018; Schmid & Doerschner, 2018). This latter ability is most likely acquired through countless multisensory interactions with objects in the environment, where simultaneous activation of visual and haptic senses leads to strong associations across modalities (Lacey, Flueckiger, Stilla, Lava, & Sathian, 2010; Yildirim & Jacobs, 2013; Desmarais, Meade, Wells, & Nadeau, 2017). For example, while exploring a type of fabric (e.g. silk or wool), its optical properties and the way it folds and deforms (i.e. its shape) might become associated with a particular perceived softness. This association can become so strong that when looking at an image of a material that has optical and shape properties that strongly resemble the originally experienced fabric, it can elicit the same “sensation” of soft (also see Anderson, 2011; Schmidt et al., 2017; or Schmid & Doerschner, 2018, for a discussion of this potential association route). This might also explain why there

is a high degree of consistence between visually tactile perceived material properties (Baumgartner et al., 2013; Vardar et al., 2019). However, to some degree this overlap is surprising, because of the inherently different information that is available in each sense. Whereas visual stimulus is basically a distal extended intensity pattern (image) that often changes across time (unless we look at a static image), haptic information is proximal, inherently serial, point by point, and contains also direct signals about the applied force.

In this experiment, we asked whether perceived softness from visual images and movies is comparable to perceived softness from haptic interactions (Cavdan et al., 2021). The most important finding is that not just haptic, but also visually perceived softness is a multidimensional construct. Consequently, one should keep this in mind when asking participants to judge the “softness” of materials or objects in perceptual experiments. A second important result is that the haptic perceptual space is more differentiated (5 dimensions) than the visual ones, with the dynamic visual space (4 dimensions) resembling the haptic space more closely. Overall, we found beyond these differences in differentiation also very good agreement between the perceptual spaces yielded by visual and haptic experiments, which is also in line with earlier studies comparing texture perception across visual and haptic domains (Binns, 1937; Lederman & Abbott, 1981; Bergmann Tiest & Kappers, 2007; Stilla & Sathian, 2008; Baumgartner et al., 2013; Xiao et al., 2016; Vardar et al., 2019).

In particular, we found three softness dimensions: surface softness, granularity, and viscosity that were common to all conditions. Although the amount of

agreement between visual and haptic experiments is substantial for the softness dimensions of surface softness, granularity, and viscosity, [Table 1](#) also shows several interesting differences between these conditions, which we will review next.

Differences in dimensionality

The individual principal component analyses revealed three softness dimensions: surface softness, granularity, and viscosity in all three conditions (static visual, dynamic visual, and haptic). However, in dynamic visual and haptic conditions, also the dimension deformability emerged, and roughness emerged as a fifth dimension in the previous haptic experiment.

Why might deformability not have emerged as a separate dimension in the static visual condition? The deformability of a material is related to its kinematic properties and can therefore in static images only be judged from shape or texture cues ([Schmidt et al., 2017](#); [Schmid & Doerschner, 2018](#); [van Assen et al., 2018](#)) or by association ([Schmidt et al., 2017](#)). Association, however, relies on two conditions: (1) the material has to be familiar, and (2) the familiar material has had to be judged on the same attribute before. This might, however, not have been the case for many attribute-material combinations: participants might have never judged the elasticity of cranberries before and could thus not rely on their previous experience. Instead, they had to rely on the available image information (shape and texture cues), which might have highly overlapped with those used for surface softness. In contrast, dynamic visual information can convey the deformability of a material much more convincingly ([Bouman et al., 2013](#); [Bi & Xiao, 2016](#); [Schmidt et al., 2017](#); [Bi et al., 2018](#); [Schmid & Doerschner, 2018](#); [van Assen et al., 2018](#); [Alley et al., 2020](#)), in particular, if also manual interactions with the material are shown ([Cellini et al., 2013](#); [Drawing & Kruse, 2014](#); [Paulun et al., 2017](#); [Yokosaka et al., 2018](#); [Wijntjes et al., 2019](#)).

Why might roughness not have emerged as a dimension in the visual conditions? In the present study, there may have only been a limited number of adjectives that were strongly associated with the roughness dimension, namely smooth and rough. In haptics, roughness is a known as a particular salient dimension (e.g. [Okamoto et al., 2013](#)), the value of which is quickly processed from the information gathered through the finger pads ([Lederman & Klatzky, 1997](#)). Thus, also with only limited measurement sensitivity, roughness can be detected as a haptic dimension. However, visually roughness is a much less salient and important dimension, and hence we might have missed to detect visually associated roughness in the present experiment. Indeed, visual ratings on roughness-related adjectives were not very variable across materials or used for

dimensions other than roughness. Previous research on roughness perception found high correspondence between vision and touch ([Brown, 1960](#); [Björkman, 1967](#); for a review, see [Lederman & Klatzky, 2004](#); [Bergmann Tiest & Kappers, 2007](#)). However, tactile information, tended to be weighted more than visual information when the roughness information is mismatched between the two modalities ([Guest & Spence, 2003](#); [Whitaker, Simoes-Franklin, & Newell, 2008](#); [Eck, Kaas, Mulders, & Goebel, 2013](#)), or while matching abrasive papers ([Lederman & Abbott, 1981](#)). [Guest and Spence \(2003\)](#) even reported a lack of visuo-tactile interactions for finer roughness stimuli. It could be that such fine texture information might have not been available in our visual conditions, which might explain the lack of a roughness dimension in the visual conditions. This would be consistent with the view that touch is superior to vision when detecting finer surface textures ([Heller, 1989](#)).

Differences in the perceptual softness space structure

With a combined PCA we were able to zoom in on differences among static visual, dynamic visual, and haptic spaces for the softness dimensions common to all three: surface softness, granularity, viscosity, and roughness. As can be seen in [Figure 4](#), the overall pattern that emerged when correlating the Bartlett scores among the three spaces (across all 4 dimensions) was that the two visual spaces were highly similar, however, only when compared to the static-haptic correlation; dynamic-haptic spaces correlated just as high as the two visual spaces. However, we also noted some differences to this general pattern when looking at the Bartlett score correlation across spaces for each individual perceptual dimension, especially with respect to the latter finding. For example, whereas surface softness was numerically consistent with this general trend (see [Figure 5](#)), there was no significant difference in the correspondence between spaces. For viscosity, there was a trend for the correlation between dynamic visual and haptic spaces being stronger than that between dynamic visual and static visual spaces. What might be the reason for this? Inspecting [Figure 3](#) might provide a hint: the Bartlett scores of the material stress balls show high values in viscosity of haptic and dynamic visual spaces but not in the static visual space. Stress balls, although being quite squishy and sticky to the touch, in their “resting” shape, do not convey these properties strongly. Therefore, the shape of the material might cause the visual system to activate a not-so-viscous material association ([Schmidt et al., 2017](#)). This emphasizes the potential relevance of dynamic visual information in transporting viscosity.

Although it is undebated that static images can successfully convey information about viscosity, they do so primarily via (shape) association. However, when the shape is unfamiliar or unusual, static images might fail to unambiguously convey the viscosity of a material.

Another exception to the described overall correlation pattern was found for granularity. Here, the correspondence between the two visual conditions was marginally higher than between dynamic visual and haptic spaces. This suggests two things: (1) granularity can be judged well and consistently from images, with observers likely using the size of individual items (sand corns, lentils, pebbles, etc.), which would be available both in static images and videos; and (2) these visually estimated properties differ somewhat from those estimated by touch. This could be because vision might strongly rely on particle size while touch might additionally consider interaction characteristics of the particles (e.g. how well they can be run through the fingers or be rotated).

Differences in ratings

Our interpretations above suggest that the differences that we find among the perceptual softness spaces of static visual, dynamic visual, and haptic conditions might be particularly driven by some special material-adjective combinations in our experiments. In order to sift these out, we identified the conditions that yielded the largest rating differences across conditions. Those material-adjective combinations that yielded rating differences between conditions will be discussed next.

Extreme distances in haptic-static and haptic-dynamic

Material adjective combinations in this group appears that material information conveyed by vision and haptics diverged. In those cases, we see that this pattern emerged primarily for judgments related to the granularity and surface softness. We already offered an explanation about the differences between visual and haptic perception of granularity above. Why do we, however, not see such differences for granularity judgments of sand? One reason for this could be sand or salt are materials that most observers are very familiar with, and when identifying the materials, prior experiences with the material might become activated enabling participants to make these judgments (Kangur, Toth, Harris, & Hesse, 2019; Metzger & Drawing, 2019). Conversely, it is possible that, when judging the granularity of lentils, pebbles, or cranberries, such a prior experience is not available and therefore participants are left with visual information “only,” which might lead to different perceptions.

This kind of argument could also apply for judgments of surface softness. Figure 6 shows that the differences between visual and haptic conditions are generally positive suggesting that felt, fur, and linen were judged to be more soft, hairy, and velvety, respectively, when interacted with. In a sense, the experiences of surface softness tend to be lower from visual images, which highlights the special role of interactive touch for perceiving this material quality.

Extreme distances in haptic-static

In contrast to the first group, adjective-material pairs in this group elicited similar judgments in dynamic visual and haptic conditions. Why did static visual information yield different ratings than haptic condition? Figure 7 illustrates that this kind of pattern emerged primarily for judgments of surface softness (how soft), but also for judgments of deformability (how elastic and how hard), or viscosity (how moist and how wobbly). The fact that surface softness occurs also in this group is unexpected, as we have just concluded that softness tends to be lower from any type of visual information, compared to that from haptic experience. It appears that we will have to modify this statement. One way to reconcile the data from Figures 6 and 7 is to consider the stimuli in the dynamic visual condition. The movies contained three sets of cues to material properties: (1) pictorial cues, (2) deformation cues, and (3) interaction cues. Whereas pictorial cues must have played a predominant role in the difference pattern of the first group (i.e. haptic and visual information each convey different material qualities), we believe it is the second set of cues that might be responsible for the higher similarity between dynamic visual and haptic ratings. This is in line with the example for elasticity (or hardness) rating of stress balls in the section above, but similar arguments can be made for judging the wobbliness of cranberries or the softness of sand. Why deformation was not effective for the first group of material-adjective pairs, would be an interesting question to pursue in future research.

Extreme distances in haptic-dynamic

This occurred just for five material-adjective pairs, but it was a highly interesting pattern, as it was in contradiction to our hypothesis, that dynamic visual and haptic conditions should yield more similar outcomes. Why might haptic and static visual conditions yield more similar ratings? One interpretation is that static images triggered associations of material qualities that were similar to those experienced through haptic exploration. It is possible that — in contrast — dynamic visual stimuli showed either deformation of interaction cues that elicited a slightly different

activation of material properties. Why might this be the case? We have shown, for example, in previous work (Cavdan et al., 2019; Cavdan et al., 2021) that exploratory hand movements not only vary with the material being explored but also as a function of the task (i.e. what is being judged while exploring a material). When selecting the stimuli for the dynamic visual condition we focused on the most frequent hand movement for a material type, neglecting the effect of task (because it was a smaller affect in our previous work). For example, for lentils, we only used the hand movement run through, yet people might need to see rotation in order to understand how smooth lentils are. It might be that this very subtle factor might have influenced observers' judgments in the dynamic visual condition. This possibility could be explored in future work. However, given the small number of cases the pattern needs to be confirmed beforehand.

Representing softness across modalities

How we visually or haptically perceive objects is profoundly affected by our multisensory prior experiences with the object/or similar objects (Witzel, Valkova, Hansen, & Gegenfurtner, 2011; Metzger & Drawing, 2019; Zoeller et al., 2019; see Rock, 1985 for a review). Over time, multisensory experiences may lead to the formation of a semantic category for a particular material, entailing all its visual and haptic properties and variations thereof. Thus, when a particular semantic category is activated, such as “squash ball,” both visual (small, round, and rubbery) and haptic (elastic and high-friction surface) properties might also become activated and can be recalled. Moreover, if information of only one modality would be available (e.g. visual), category activation would allow us to also make haptic judgements, based on visual information alone. For instance, when we visually recognize a squash ball as such, even without handling, we know it is much more deformable than a petanque ball. If, however, an object or material is unfamiliar, category knowledge is not available (e.g. not knowing or recognizing the petanque ball), then we have to rely on the sensory input (e.g. we perceive a sphere, but it might be ambiguous whether it is hard or soft, especially if we are only provided with a static image of the ball).

In both cases, not knowing/recognizing an ambiguous sensory information, we would expect to find differences in the dimensionality of softness in visual and haptic domains. This difference could potentially be reduced or eliminated in the first case (knowledge): for example, by familiarizing the participants with all materials prior to the experiment. If, however, the difference arises from the ambiguity of the visual information

then prior familiarization might not be as effective in eliminating differences if softness dimensionalities between modalities. This could be investigated in future experiments.

Several scientific disciplines and applied fields are interested in understanding how humans perceive materials through vision and touch or how realistic experiences of material interactions can be created (e.g. via augmented or virtual reality). Although many previous studies have used computer-rendered (for visual experiments) or somewhat uniform stimuli (e.g. silicone with different degrees of compliance for haptic experiments), we have used natural, and real-world materials in our experiments. Whereas experiments using computer renderings and unidimensional haptic stimuli have a high degree of control and certainly provided important insights, they do lack some ecological validity, and results from such experiments may not fully be representative of our day-to-day visuo-haptic experience of materials in the world. Using real materials, we were able to show that perceiving softness from photographs and movie clips of real materials has a similar dimensionality as haptically perceived softness. Yet, we also found that for some materials and attributes visual information may lead to somewhat different assessments about material qualities than haptic information (see Figure 6), and yet, in other cases, dynamic visual information (showing interactions with materials) might be quite effective in communicating the haptic experience (see Figure 7). This result is potentially valuable for researchers, engineers, or designers who aim to optimize the visual depiction of a particular material quality. In future experiments, it would be interesting to find out how a specific kind of softness is optimally (with respect to the haptic sense) conveyed in static and moving images and based on this data to develop an image-computable model that allows us to parametrically manipulate, for a given material, the degree of expression along each softness dimension.

Conclusion

Softness is a prominent property that renders an object useful or useless, appealing, or repulsive to us. Results of this study confirm that perceived softness is a multidimensional construct. This should be taken into consideration when asking participants to make judgments about the softness of materials in research or applied contexts. This multidimensional softness space is similar for visually and haptically presented materials, however, results also suggest that there might be some noteworthy differences between these modalities. We suggest that these differences might appear primarily emerge when participants cannot draw on previous

visuo-haptic experiences with a material for a particular judgment, or when visual cues are ambiguous to the material property in question.

Keywords: material perception, softness, haptics, vision, granularity, viscosity

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Corresponding author: Müge Cavdan.

Email: muege.cavdan@psychol.uni-giessen.de.

Address: Department of General Psychology, Otto-Behagel-Str. 10F, 35394 Giessen, Germany.

Footnote

¹In addition, auditory cues play a role in material perception, however these are not the focus of this investigation (Klatzky, Pai, & Krotkov, 2000; Fujisaki, Goda, Motoyoshi, Komatsu, & Nishida, 2014; Fujisaki, Tokita, & Kariya, 2015).

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