Perception of mechanical material qualities through haptic and visual explorations

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To my grandfather

my role model, hero

who guided me through my journey to become the person I am!

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Abstract

Material perception is a crucial part of our everyday life. This is more evident, when deciding where to put our step forward while walking under the rain or when applying enough force to a soap to grasp it without it slipping through our fingers. Over the past decade, material perception attracted increasingly more attention. Yet many questions remain unanswered. Material perception is a complex problem with numerous entry points. For instance, in haptic research, softness is generally equated to the compliance of the objects. However, a recent study has shown that this is not the only case. Perceived material dimensions underlying softness (Dovencioglu et al., 2021) include granularity, viscosity, surface softness, and deformability of the materials. Moreover, people adapt their hand movements according to the material. Another open question would be in addition to extrinsic material properties whether our purpose (i.e., information to be gained) affects hand movements when haptically perceiving different softness dimensions. To this extend, in Study 1 we investigated whether the task and the explored material modulate the exploratory movements. Firstly, our findings replicated the previously reported multiple perceptual dimensions of softness (Dovencioglu et al., 2021). More importantly, our results extend the literature by showing that people adapt their movements based on the material, task, and the interaction between the two.

Another entry point to the material perception would be to ask how different modalities provide information on the same material. In daily life, we usually see what we touch and touch what we see. Whether vision provide similar information to haptic about the various aspects of softness is an intriguing question. For instance, in order to judge the softness of a rabbit's fur, we can inspect its softness by looking at a picture or by touching the rabbit's fur. Another source of information could be, watching someone else petting the rabbit. In contrast to the merely looking at the rabbit's fur, watching someone else's action not only provides the visual feature of the fur but also reveals how the material reacts to the hand movements. It is elusive whether these three examples would yield similar interpretations of softness as a multidimensional construct or not. In Study 2, we investigated to what extent the perceived softness dimensions are similar in vision

compared to haptics. Our results showed high overall consistency across haptics, static visual information (i.e., images), and dynamic visual information (i.e., hand movement of other exploring materials). These similarities were the strongest between availability of haptic and dynamic visual information.

In our daily experience, we do not only touch objects with bare hands but also sometimes through intermediate surfaces (e.g., wearing gloves). Perceiving materials over another layer of material could reduce some of the haptic information such as thermal properties of the material in question. Despite our regular interaction with materials under restrained conditions (i.e., wearing gloves in winter), it is mostly unknown to what extend these restrictions affect our perception of different aspects of softness. Therefore, another entry point to understanding material perception would be to understand how material perception is affected by physical constraints. It is almost ironic that the augmented or mixed reality technologies for haptics generally construct the haptic experience through gloves or other restrictive proxies. Hence, understanding how physical constraints affect material perception is an important question concerning both theoretical and practical research. In Study 3, we seek to understand how haptic constraints affect perceived softness. Participants explored haptic stimuli under four conditions: bare hand, open-fingered glove, open-fingered glove with rigid sensors, and full glove. General results suggest that softness perception was overall highly similar across conditions. However, in a closer inspection, we found that glove condition differed from the others especially in terms of surface softness.

So far, the discussed entry points to material perception scrutinized the material perception in sensory domains. However, as in other topics in perception, the material perception - in addition to the sensation - depends on the agent's cognitive state such as their motivation, emotion, etc. In a similar vein, the previous studies have shown that sensory and affective properties are related. For instance, fine grained materials like sand feel pleasant while rough materials such as sandpaper feel unpleasant (Drewing et al., 2018). The origin of these relationships is another piece of the puzzle. To remedy this gap, in Study IV, we investigated whether the relationship between sensory materials properties (i.e., granular) and affective responses (i.e., feeling pleasant) can be modified by learning. We further investigated previously observed relationships: positive relationship

between granular and pleasantness, negative relationship between roughness and valence. With a classical conditioning paradigm, instead of participants' existing material-emotion associations the opposite affective relationship was reinforced. The results have shown a significantly decreased relationship between valence and granularity in the experimental group compared to the control group. However, valence and roughness relationships did not differ between the experimental and the control groups. The results suggest that not all affective associations of the perceived material dimensions could be modified. We explain these results with the difference in learned and hard-wired connections.

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List of Abbreviations

EP: Exploratory procedures

AR: Augmented reality

PCA: Principal component analysis

SA: slow adapting

FA: fast adapting

SVM: support vector machine

1. Introduction

The material properties of the everyday objects vary greatly. Therefore, recognizing these properties is an essential part of object recognition. One important factor determines how we interact with objects is their underlying material properties (Dovencioglu, 2021). For instance, if the object to be touched is fragile, this object should be approached delicately. Similarly, the way we interact with an object also changes with our purposes and intentions (Lederman & Klatzky, 1987) such as applying pressure to an avocado to understand its ripeness. In summary, material perception has a key contribution to our everyday doings with objects. However, material perception is not a straightforward given. On the contrary it involves a myriad of information, redundant or complimentary, from available modalities. Keeping the same example, when assessing the ripeness of an avocado, we have access to its visual, haptic, and olfactory properties. Yet only a limited number of features such as color, pressure, absence of bad smell serves our purpose. Hence, understanding how effective these factors are across different modalities is an important step to understand multisensory interactions.

To this end, this thesis investigates sensory and affective components of materials. To be more precise it poses the following questions: 1) how the material and the task affect exploration style when perceiving softness 2) whether vision can provide similar information about different aspects of perceived haptic softness 3) investigate whether different haptic restrictions affect perception of soft materials 4) investigate the source of targeted perceptuo-affective relationships. It aspires to explore these questions with four experiments reported here. Before presenting the results of these studies, it is necessary and beneficial to establish these questions within the literature. Therefore, next section will be focusing on material perception to provide an overview.

Material Perception

We are constantly in touch with the materials around us. Therefore, figuring out on which materials are the objects made out of and acting upon their corresponding properties constitute a substantial portion of our daily routines. Thus, the perceived qualities of materials guide us to make critical decisions on how to interact with them. Examples demonstrating how material perception shapes our daily life decision include judging the ripeness of an avocado or the comfort of a sofa that we intend to buy. If the sofa is not soft enough, you probably would not want to buy it. This is simply because the rough surface feels uncomfortable. Daily as if may material perception is complex. Even a simple sofa example showcases that materials do not only compose of sensory (i.e., roughness) but also affective properties (i.e., uncomfortable, or negative). Hence, this thesis' approach to this matter will be providing evidence on the sensory and affective components of material perception. However first it is important and equally necessary to individually define these two components.

1.1. Sensory Properties of Materials

Humans are sensitive to a myriad of sensorial material properties; optical (e.g., translucency, color, and glossiness), mechanical (e.g., softness, roughness), chemical (e.g., rusted metal surface), and thermal (e.g., melting point) to name a few. Whitaker et al. (2008) suggested that optical properties of materials (e.g., gloss) ideally conveyed by vision while mechanical properties such as softness by touch. However, it is often the case that material perception is multisensory, hence includes complementary or redundant information from different modalities. Indeed, we make use of these information from different modalities. For example, when we go to a store to buy a clothing or any other fabric, we do not just look at it. Instead, almost instinctively we touch and feel their surfaces.

1.1.1. Haptic Perception

As the above example demonstrates haptic sensing (haptics) is crucial to our daily life experiences. Haptic perception is typically defined as active manual exploration of objects and surfaces (Lederman & Klatzky, 2009). It relies on two afferent subsystems which are cutaneous and kinesthetic (Purves et al., 2004). Kinesthetic sense receives sensory information from the receptors located within the joins, muscles, and tendons (i.e., Golgi tendon and muscle spindle). Muscle spindles located within the belly of muscles which stretches with muscle movement, detect changes in the length, and carries information to the central nervous system (Mileusnic & Loeb, 2006). The Golgi tendon lies between muscle tendons and muscle fibers. It is a proprioceptive sensory receptor which senses the changes in the muscle tension (Purves et al., 2018). Whereas cutaneous receptors receive sensory information from the receptors embedded in the skin which are located in dermis or epidermis and part of the somatosensory system. Specifically, these receptors are cutaneous mechanoreceptors, nociceptors (i.e., pain), and thermoreceptors (i.e., temperature). Thermoreceptors, as their name suggests, are specialized to transduce changes in temperature. Cold-sensitive thermoreceptors cause the sensations of cold, freshness, and cooling while the remaining thermoreceptors have the opposite function by triggering heat or even rarely burning sensations. Nociceptors are sensory neurons that send possible threat signals to the brain and spinal cord when interacting with damaging or potentially damaging stimuli.

There are four types of highly specialized mechanoreceptors in human glabrous skin to procure information about pressure, vibration, cutaneous tension, and touch to the central nervous

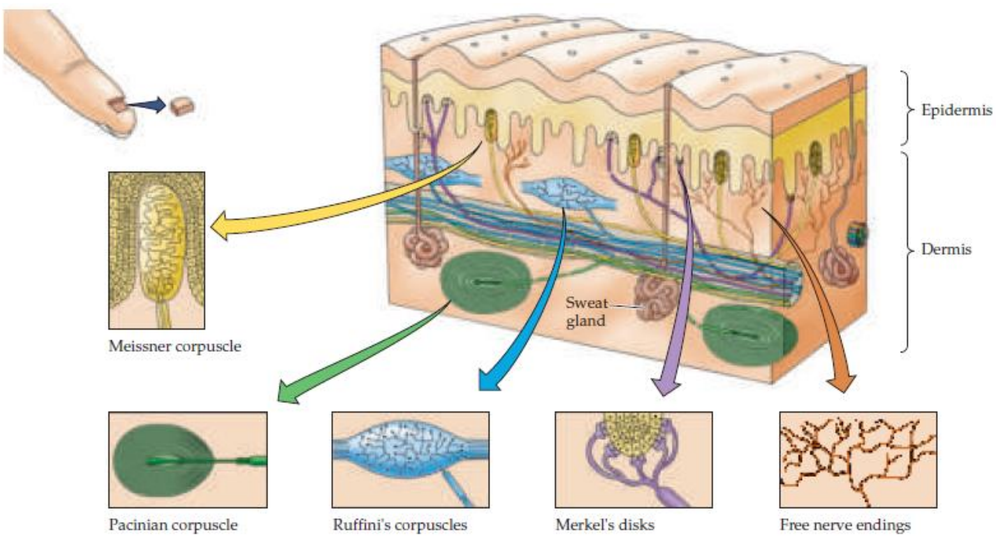

Figure 1.1. The diagram of the smooth glabrous skin of the fingertip. It highlights the mechanoreceptors in the skin of the hand which are Meissner corpuscle, Pacinian corpuscle, Ruffini’s corpuscles, and Merkel’s disks (from Purves et al., 2004).

system. The density of the mechanoreceptors increases in distal direction from palm to fingertips. Therefore, the distal phalanx is the area where the mechanoreceptors are highly dense (Johannsson & Vallbo, 1978). Mechanoreceptors are classified according to the size of receptive field and the adaptation speed of a receptor when a constant pressure is applied (Vallbo & Johansson, 1984). Receptive field size depends on number of sensory cells which are connected to a specific nerve fiber and grouped into two: small (usually marked as I) or large receptive fields (usually marked as II). One common way of categorizing mechanoreceptors is the adaptation behavior which consists of two classes: slow adapting (SA) or rapidly adapting (RA or sometimes FA). Mechanoreceptors are Pacinian corpuscles (receptor type: RAII/PC/FAII), Merkel's disks (receptor type: SAI), Ruffini's corpuscles (receptor type: SAII), and Meissner's corpuscles (receptor type: RAI) (see Figure 1.1). While Meissner's and Pacinian corpuscles are rapidly adapting Merkel's disks and Ruffini's corpuscles are slowly adapting cutaneous mechanoreceptors.

Meissner's corpuscles are the most common and rapidly adapting mechanoreceptors of glabrous skin. When a textured object is moved across the skin, they efficiently transduce information on low-frequency vibrations (30-50 Hz). Thus, they detect changes in texture and adapt quickly. Pacinian corpuscles are onion like shaped and even faster adapting than Meissner's corpuscles. Pacinian corpuscles are highly sensitive to mechanical transient and high frequency vibrations (250-400 Hz) and they are responsible from detecting rapid vibrations. Similar to Meissner corpuscles, they encode dynamic information of mechanical stimuli as well as play a role in discriminating fine surface textures. In contrast to Meissner and Pacinian corpuscles, Ruffini's corpuscles and Merkel discs are sensitive to pressure. (Johansson & Flanagan, 2009).

The information received from the mechanoreceptors of the skin reaches thalamic nuclei and proceeds to somatosensory cortices (SI: primary somatosensory cortex and SII: secondary somatosensory cortex). We already have a good idea how the somatotopic map of the brain looks like (Figure 1.2). Neuroimaging studies have shown that different brain regions involved in tactile processing of different object properties (Roland et al, 1998; Stilla & Sathian, 2008; Sathian et al., 2011; Kitada et al, 2019). For instance, touching a texture activates parietal operculum, insula, and occipital cortex more than perceiving object shape by touch (Stilla & Sathian, 2008). Kitada et al. (2015) and Eck et al. (2016) found that the activity in insula and parietal operculum is related to the perceived roughness magnitude. More recently Kitada et al. (2019) have shown that different brain regions involve in softness perception which are parietal operculum, insula, postcentral gyrus, posterior parietal lobule, and middle occipital gyrus.

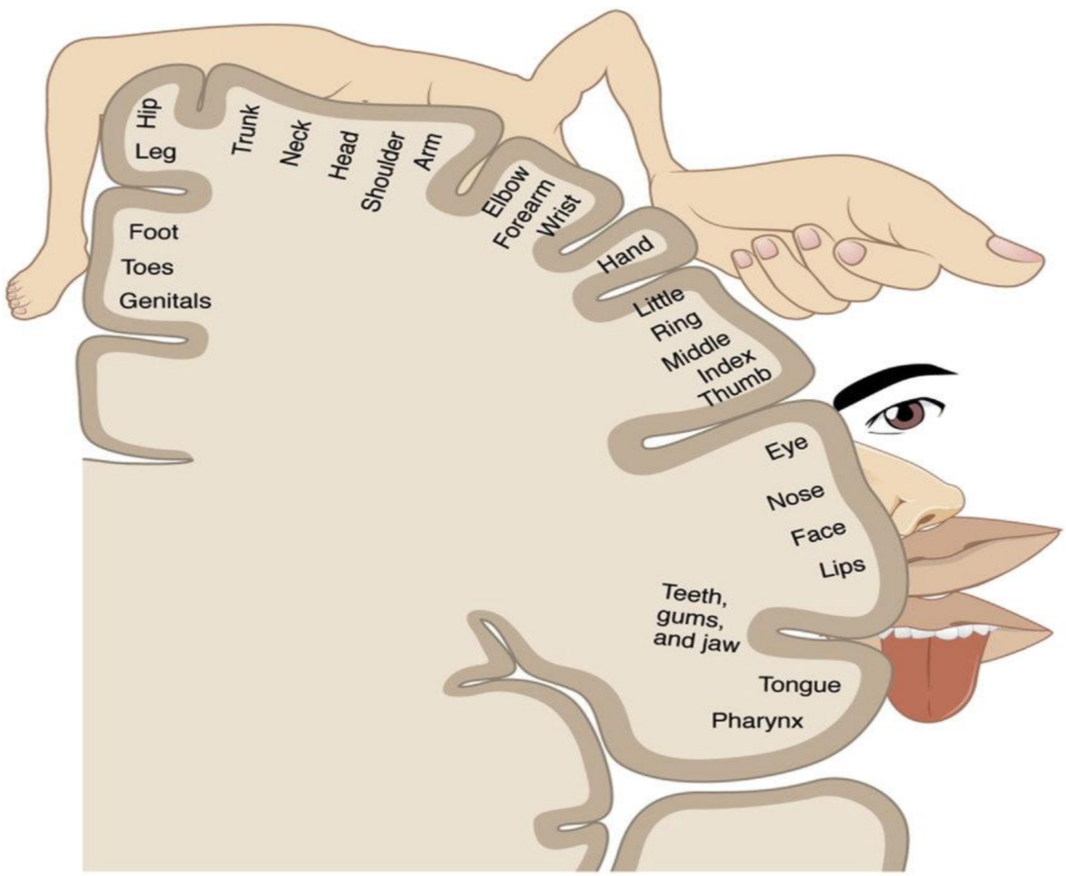

Figure 1.2. Somatosensory cortex homunculus. Larger areas of the cortex are occupied mostly by the body parts with highest tactile sensitivity. Retrieved from Open Stax College, Illustration from Anatomy & Physiology, Connexions Website. http://cnx.org/content/col11496/1.6/, March 16, 2021.

Our understanding of how different types of information are received from skin sensors and where they processed in the brain greatly improved compared to the last century. However, the psychophysical dimensions of touch is another story. The following section addresses this matter with an emphasis on softness perception.

Psychophysical Dimensions of Tactual Textures

When we touch materials or textures our sensory system collects physical information, but this information is processed and transformed into a percept. The psychophysical component of this percept (other being the affective component) is associated with the physical properties like the surface roughness or the stickiness of materials. In a review article, the psychophysical tactual dimensions of the textures have been categorized by Okamoto and his colleagues (2013) in five main dimensions which are warmness (cold/warm), hardness (hard/soft), micro and macro roughness (/smoothness), and friction (moistness/dryness). These dimensions are described and studied as follows.

Roughness. Roughness is one of the most studied object properties in haptic perception. Roughness physically refers to the height differences of a surface which can be measured with profilometer (Bergman-Tiest, 2010). However, operational definition of it changes from experiment to experiment depending on the stimulus set. In general terms when a rough surface is stroked it causes uneven pressure distribution on the skin. In one of the early studies, Meenes & Ziegler (1923) asked about participant's experience when they were touching papers with different surfaces. During static touch, they reported unevenness of pressure. However, during active touch participants reported smoothness and roughness. Similarly, Katz (1925) reports an experiment where participants differentiated between papers with and without movement. He found sense of vibration to be more defining than pressure for roughness perception. More recently, by adopting a similar task, Hollins & Risner (2000) showed that in the static touch condition, perception got worse for textures with element size below 100 μm. They argue that static condition only provides pressure cues, dynamic condition provides both pressure and vibration cues. This difference between active and static touch captured by the duplex theory (Hollins & Risner, 2000). Therefore, for the coarser textures above 100 μm particle size only pressure cues might be enough. Suggesting that the mechanisms are involved in perception of micro and macro roughness are different. Consequent studies divided roughness into two dimensions: micro and macro roughness (Picard et al., 2003; Gescheider, 2005). Neurophysiological studies have shown that SAI units contribute to roughness perception (i.e., rougher surfaces) because of the spatial distribution of SAI units (Connor et al., 1990; Blake et al., 1997). For the perception of finer textures however, vibration cues are crucial. Thus, (this is shown by) that FAI and FAII units are associated with the perception of fine roughness.

Warmness/Coldness. The perception of warmness/coldness refers to the successful heat transfer between a texture and finger skin (Pac et al., 2001; Jones & Ho, 2008). Successful heat flow between finger pad and material is very important for material recognition (Katz, 1989). However, an object's temperature is different from the warmness/coldness of an object at room temperature. Perceived coldness/warmness of a material is related to the intensity of heat extraction from fingers while touching a material (Havenith et al., 1992). This highly depends on thermal properties of a material like object's geometry, specific heat, and thermal conductivity (Bergmann-Tiest, 2010).

Friction. It has been suggested by Okamoto et al. (2013) that the perception of stickiness/slipperiness and moistness/dryness have been mediated by friction. They supported this argument by presenting the fact that stickiness/slipperiness and moistness/dryness have been extracted together in the studies focusing on these dimensions (e.g., Hollins et al., 1993; Hollins et al., 2000). Therefore, Okamoto et al. (2013) concluded that the two dimensions have been originated from a single dimension.

Hardness/Softness. Perceived softness (or hardness) is defined as the subjective measure of an object's compliance, the amount of deformation in an object in response to an applied force (Di Luca, 2014). Different measures can be used to define this amount of deformation under pressure. Firstly, an object's *stiffness* defined as the ratio between the normal force applied to an object and the displacement in the object's surface. There is a negative correlation between softness and *stiffness*. Therefore, *stiffness* is the inversely related to subjective compliance. However, stiffness also depends on the dimensions of the objects. For instance, a ticker object deforms more than a thinner object of the same material and stiffness (Bergmann Tiest & Kappers, 2014). Another physical measurement of the compliance is a material's *Young's modulus*. *Young's modulus* is a measure of how easily a material is bended or stretched. *Young's modulus* sometimes can be referred as modulus of elasticity which is equal to the longitudinal stress divided by the strain. The softness of an object can be detected actively through fingers by applying pressure to the surface (Srinivasan & LaMotte, 1995) or through a tool (e.g., rigid probe, LaMotte, 2000). When discriminating softness, both tactile and kinesthetic cues are shown to be necessary (Srinivasan & LaMotte, 1995). In the same study, Srinivasan & LaMotte (1995) investigated human's ability to discriminate softness of objects tactually by using silicone rubber objects with rigid and deformable surfaces. The experiment had three conditions: active touch with the normal finger (kinesthetic and tactile information available), active touch with local cutaneous anesthesia (only kinesthetic information available), and passive touch (only tactile information available). Participant's task was to rank objects based on their softness. When aestheticized finger is used people were not able to discriminate between silicone objects 90% differ in stiffness. During passive touch condition, people were not able to discriminate specimens which differ less than 75% in stiffness. These results overall suggest that cutaneous information is crucial and without kinesthetic information discrimination of softness is deteriorated.

Exploratory Procedures (EPs)

Do humans use the same hand movements for all tactile surfaces? If one thinks about handling an avocado versus a sandpaper the answer clearly presents itself. Different hand movements allow us to understand different material properties. Thus, they adapt to the information one seeks to gain. Gibson has discussed already in 1962 that human haptic perception is active and purposive. His work has been extended by Lederman & Klatzky (1987) by showing that people make use of various hand movements when exploring common objects. In this seminal work Lederman & Klatzky (1987) used a *match-to-sample task* where blindfolded participants asked to match objects on certain dimensions (e.g., texture, volume, etc.). They found humans generate stereotypical hand movement patterns while perceiving different material properties. These repetitive movement patterns are called exploratory procedures (EP, Lederman & Klatzky, 1987). Their work further shows that EPs were shaped according to the information a person seek to obtain which does not even require the knowledge of an object. The listed EPs in this study are *static contact*, *enclosure*, *lateral motion*, *unsupported holding*, *contour following, and pressure.* Each of these EPs are associated with different properties (Figure 1.3). *Lateral motion* is used to gather information on surface texture. The skin is slid on laterally a surface by producing shear force. *Enclosure* is used to understand volume or the global shape of an object. The fingers (and/or palm) are enveloped to the object surface. *Static contact* is used to understand temperature of an object. The skin is kept in close contact with the object without creating a motion by using a large surface (e.g., the whole hand) which helps to heat to flow between the object and skin. *Unsupported holding* is used to determine weight of an object. Typically, it is hefting an object with hand without any support from any surface or the other hand. *Contour following* is an EP in which the contact between the hand and a contour of an object is maintained. This EP is used to gather information about an object's exact shape. *Pressure* is used to learn how deformable an object is. It is produced by applying normal force or torque to a part of an object while rest of an object is stabilized, or force is applied in opposing direction.

The EP pressure has been used frequently in softness perception studies and has been equated with the compliance of an elastic material (Srinivasa & LaMotte, 1995; Bergmann-Tiest & Kappers, 2009; Cellini et al., 2013; Zoeller et al., 2019; Xu et al., 2020). Thus, studies investigating softness participants asked to perform specific exploration behaviors such as pressing into a surface (Cellini et al., 2013; Zoeller et al., 2019), squeezing an object (Klatzky & Lederman, 1999; LaMotte, 2000), or tapping (Higashi et al., 2018). However, the softness experience in daily life is richer and conveys more information than only compliance of an object. For instance, while stroking fluffy fur of a dog, when you squeeze hair gel to your hand, or when you take a handful of sand in your hand slide the particulars of the sand between your finger, one would feel different kind of softnesses. Thus, the type of the softness experience greatly differs from one case to another.

The last decade has witnessed abundance of studies on material perception, only few of these studies have used real life objects which can explain the difference between the daily life and lab experiences (Sharan, 2009; Baumgartner et al., 2013; Vardar et al., 2019; Dovencioglu et al., 2021). A recent study by Dovencioglu and her colleagues (2021) investigated different

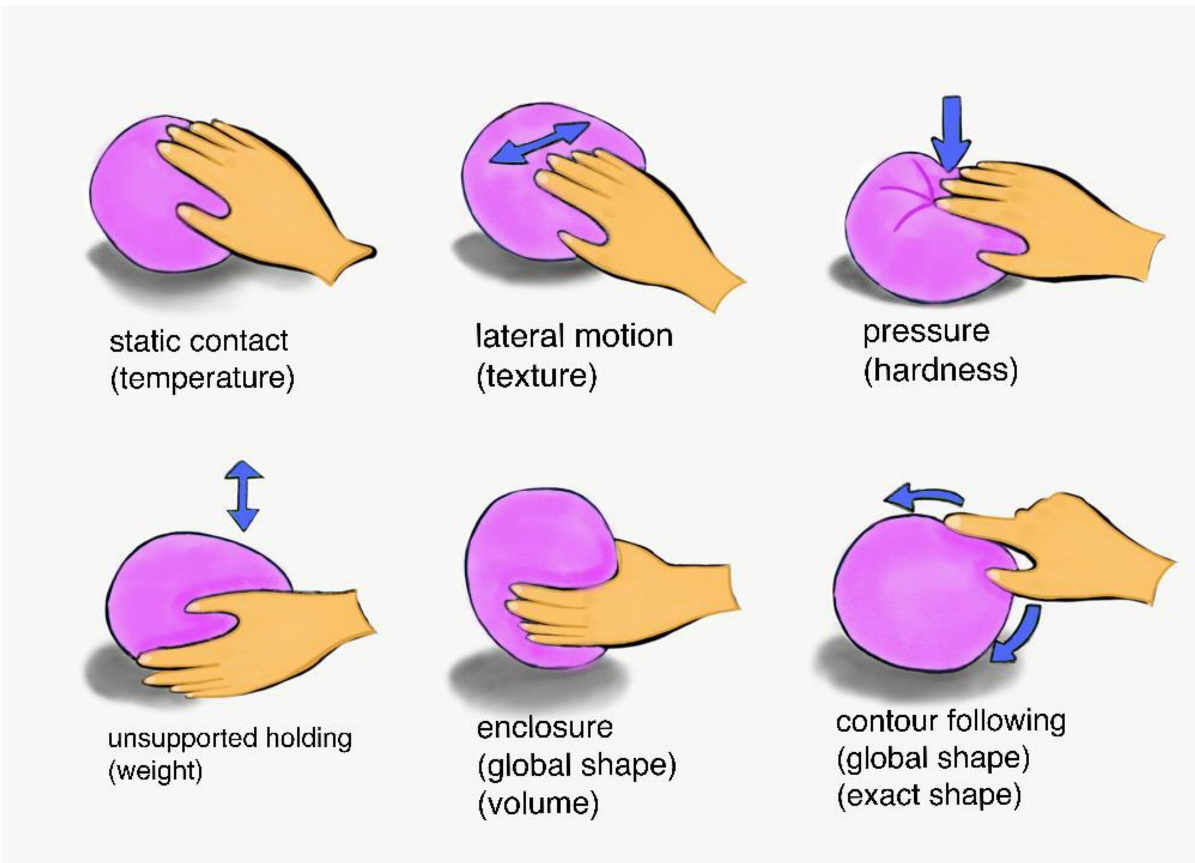

Figure 1.3. Exploratory procedures and their associated properties from Lederman & Klatzky (1987).

softness dimensions using a wide range of soft and non-soft materials and a semantic differential task. They found four dimensions of haptic softness and extracted eight different EPs from videos of people exploring soft and non-soft materials. The eight EPs were pressure, rubbing, stroking, rotating, stirring, pulling, running through, and tapping (descriptions and examples can be found in Table 2.1.). Thus, they showed that people adapt the EPs to the material being explored. However, the material properties or our purpose to explore materials (e.g., judging viscosity) are not independent from each other. In other words, people might be adapting their EPs depending on both the information to be gained and the material.

The importance of having a better ecological approach in stimulus selection extended our understanding of softness perception. Aside from materials, the haptic material perception also depends on the sensory restrictions. Even though we usually perform everyday tasks with bare hands which is the most efficient way, (Klatzky et al., 1985; Klatzky et al., 1993; Lederman & Klatzky, 2004) we interact with materials under various constraints especially when the bare hand exploration is not possible or not preferred. For instance, we use warm gloves in winter, protective gloves for work, or combine AR setups with different kinds of sensor gloves. Previous studies have touched upon the effect of free exploration restriction on object identification using glove and open-fingered glove (Klatzky et al., 1993; Lederman & Klatzky, 2004). Yet, to our best knowledge none of the studies investigated the effect of restrictions on softness perception. Exploring the material perception under hand restriction is both theoretically and practically important. The theoretical appeal is that hand restrictions such as gloves could block or reduce the skin receptors sensitivity. Absence or reduction of tactile cues could alter softness perception as in active versus passive touch. Understanding the consequences of hand restriction could help, for instance, to a doctor to better examine their patients. Another beneficiary of such research agenda would be the AR or mixed reality. Often times these technologies require hand-tracking sensors. Any development in this area potentially benefits the theoretical research by providing a tool for conducting ecological experiments.

1.1.2. Visual Material Perception

Similar to touch visual material perception is an integral part of our daily life and scientific research. Most of the research in visual perception focused on the image cues or physical factors to understand how people perceive optical properties of surfaces such as gloss and translucency (e.g., Dovencioglu et al., 2017; Adams et al., 2019; Cheeseman et al., 2021; see Chadwick & Kentridge, 2015 for a review). Therefore, the research on material perception concentrated around the interaction of optical properties and how they are perceived. For example, 3D shape (Xiao et al., 2020), color saturation (Fleming & Bülthoff, 2005), highlight-shading relationship (Motoyoshi, 2010), and lighting direction (Xiao et al., 2014) are found to affect translucency. Perception of gloss has been found to depend on multiple factors such as direction of illumination (Nefs et al., 2006; Leloup et al.,2010), specular highlights (Marlow & Anderson, 2013), and object properties (Marlow et al., 2012). These studies overall suggest that static cues are sufficient to infer optical properties of the materials.

However not every object or our interaction with them are stationary. We constantly move around and explore the environment actively. As a consequence, we rarely perceive materials in static scenes (Gibson, 1979). While different material properties have been investigated with static images (Motoyoshi et al., 2007; Sharan et al., 2008; Doerschner et al., 2010; Liu et al., 2010) human material perception is dynamic in nature. Therefore, motion is another piece of information for object perception. Yet until recently, the role of motion in visual material perception is often neglected. Motion provides more information and increases the qualities of perceived materials in both human (for a review see Doerschner, 2013) and computer vision. Thus, recent studies have shown that perception of optical properties of surfaces (e.g., surface gloss) are affected by image motion (Sakano & Ando, 2010; Doerschner et al., 2011; Yilmaz & Doerschner, 2014; Schmid & Doerschner, 2018; Mao et al., 2019).

Another gap in visual material perception is that research has mainly focused on optical properties of rigid materials, yet we interact with soft materials on daily basis and are good at perceiving mechanical properties of the materials (e.g., softness and hardness, Schmid & Doerschner, 2018; Schmidt et al., 2020). For example, while estimating mechanical properties of fabrics from different dynamic scenes, people showed highly correlated estimations with physical parameters (Bi & Xiao, 2016).

1.1.3. Visuo-Haptic Material Perception

Previous sections addressed material perception in vision and touch. However, everyday experiences with materials are often multisensory in nature. Gathering information from different senses that correspond to same material makes material perception robust but in return makes it a difficult area of research. Previous research investigated the interplay (Lederman et al., 1986; Cellini et al., 2013; Sathian, 2014) and correspondence (Gaissert et al., 2010; Baumgartner et al., 2013; Vardar et al., 2019) between vision and touch. In one hand, studies focusing on interplay between modalities usually seek to answer to questions such as how the information obtained from different modalities are integrated or which modality dominates the other. For instance, Cellini, Kaim, & Drewing (2013) investigated how haptic and visual information is integrated to judge softness of deformable objects. Their experiment featured a (i.e., which of the object is softer) vision only, haptic only, and both haptic and visual condition for discriminating deformable objects. Visual information consisted of finger movements and object deformation which was simulated using computer graphics. Haptic information consisted of applying pressure against the surface and haptic and visual condition consisted of both. Their results have shown that people were able to gather softness information from vision. On the other hand, correspondence studies examine how similar or different two modalities are. For example, Baumgartner et al. (2013) tested correspondence between visual and haptic modalities using 84 different materials (e.g., fabric, plastic, paper, wood, etc.) from several material properties. They conducted a categorization experiment with visual and haptic conditions. In the haptic condition, blindfolded participants made judgements based on haptic impressions while in the visual condition they made judgements depending on only visual explorations. They found that perceptual spaces from haptic and visual conditions are similarly organized. Also, the two components that dominate both senses were hardness and roughness. Similarly, Vardar et al. (2019) investigated how similar visual and haptic spaces are using real textures. They asked people to either touch or look at different surfaces (e.g., wood, aluminum foil, etc.) and rate similarity between two surfaces. Using multidimensional scaling method, they found that both haptic and visual spaces are similarly organized. These spaces consisted of roughness/smoothness, hardness/softness, and friction dimensions. To conclude, using different material sets Baumgartner et al. (2013) and Vardar et al. (2019) found similar findings, showing humans are good at perceiving different qualities of materials by vision and touch, and those properties are perceived similarly using visual or haptic information. However, in both experiment researchers used only static images of the selected materials. How would the availability of dynamic information (i.e., motion) in visual condition affect material perception? Would it provide additional information compared to static cues or would it be redundant?

Wijntjes, Xiao, & Volcic (2019) investigated whether movies offer better understanding of tactile properties compared to static images. They found that dynamic visual information improves the understanding of how a fabric feels compared to static visual information (experiment 1). Also, watching hand movements of others doing the same perceptual task in real life improved the estimation of material properties (experiment 3) but not watching someone who was not performing a perceptual task (experiment 2). Therefore, purposive hand movements might be providing more information on different material properties than recordings of the same hand movements for every material. For instance, observers can judge the weight of lifted objects by observing the lifting motion (Bingham, 1987; Hamilton et al., 2004; Auvray et al., 2011; Maguinness et al., 2013). In a similar vein, humans can distinguish compliance by observing someone else's finger motions (Cellini et al. 2013; Drewing & Kruse, 2014). In fact, when we do not have access haptic information, observing someone else's hand movements might cause similar percept as touching the same object.

In a recent study Yokosaka et al., (2017) investigated if people can estimate how others feel about a textured tactile material by only observing someone else's hand motion extracted from tactile explorations. In a psychophysical experiment they had two different sessions: observer (i.e., visual stimuli) and toucher session (i.e., tactile stimuli). In the toucher's session people explored the tactile stimuli while experimenters recorded their hand movements. Their task was to make tactile ratings. In the observer's session participants watched the point-touch hand movements of others from the toucher's session and made tactile ratings. Tactile ratings consisted of rating different material categories (i.e., glass, stone fabric, wood, rubber, paper, plastic) on different surface attributes (i.e., hardness, roughness, stickiness, and warmth). Yokosaka et al. (2017)'s results overall shows that humans can estimate tactile perception through visual observation of other's hand movements in various material categories.

Taken together, motion seems to contribute to the perception of different material qualities through visual explorations. Thus, seeing someone else explore materials might not only gives us information on different materials qualities, but it might also provide some information we receive only by touching the objects.

1.2. Affective Properties of Materials

While touching materials, in addition to the psychophysical properties, humans show affective responses (Chen et al., 2009; Chen et al., 2009; Drewing et al., 2018). Okamoto et al. (2013) suggested that tactile perception consists of two layers: psychophysical and affective. So far, I focused on the sensory aspects of the objects. Based on our daily life experiences one can imagine that touching rough objects such as bark feels unpleasant whereas touching soft objects like fluffy rabbit feels pleasant.

Before introducing the research on affective properties of the materials it is important to briefly define what an affective response is. Three-factor theory of emotions (Russel & Mehrabian, 1977) suggests that three independent and bipolar dimensions are necessary to appropriately define affective states. Valance, arousal, and dominance are the basic affective dimensions where each dimension consist of two opposite poles. Valence is the affective quality of an object or an event (Fox, 2008). For instance, affects such as anger and sadness are attributed as "*negative*" and refers to negatively valanced affect. In contrast, affects like happiness or joy are attributed as "*positive*" and refers to positively valanced affect.

In different theoretical grounds various kind of terms have been used to refer to the arousal dimension some of which are *activation*, *tension*, *energy*, or *activity*. However, despite the use of different terminology, what was intended to refer is almost the same. Arousal is often described as the amount of available energy one can feel. It ranges from sleepiness and drowsiness (low arousal) to vigilance which is accompanied by excitement (high arousal) (Russel & Feldman, 1999). On a basic level, arousal can be defined as the strength of an affect. Affect can be high or low arousal regardless of the valence (i.e., positive or negative). For instance, while happiness has positive valence and high arousal, fear, disgust, and anger have negative valence and also high arousal. Dominance ranges from dominant to submissive. Although both anger and fear are negatively valanced, anger is a dominant affect while fear is a submissive affect.

Majority of the research makes use of affect in haptic perception has focused on the relationship between pleasantness (i.e., valence) and the perception of different sensory dimensions. For instance, Guest et al. (2011) found that soft and smooth materials are related to more pleasant feelings than rough materials, and the rougher a material is the more it feels unpleasant. However, as mentioned above, affect does not only compose of valence but also dominance and arousal. More recently, Drewing et al. (2018) systematically investigated the relationship between sensory material properties and all three basic affective dimensions (i.e., valence, arousal, and dominance). In their experiment, participants explored a diverse set of solid, fluid, and granular materials, manually without any restrictions. After the exploration of each materials, participants had to rate the material based on different sensory and affective adjectives. Based on PCA, they extracted six sensory dimensions (*fluidity*, *roughness*, *deformability*, *fibrousness*, *heaviness*, and *granularity)* and three affective dimensions (*arousal*, *valence*, and *dominance*). They found positive correlation between *fluidity* and *arousal*, positive correlation between *dominance* and *heaviness*, and negative relationship between *dominance* and *deformability*. Also, positive valence was related with increased *granularity* and decreased *roughness*. Although these perceptuo-affective relationships are found in the literature, it is unknown whether these relationships are due to learning experiences or innate mechanisms. Being able to find the source of these relationships will enable us to manipulate them and contribute to several research and applied fields.

1.3. Outline

The aim of this thesis "*Perception of mechanical material qualities through haptic and visual explorations*" was to shed light upon the effect of different sensory and affective aspects on material perception. In Study I, we investigated whether people adapt hand movement to their task and material when haptically perceiving different dimensions of soft materials. Study 2 compares haptic perception of soft materials in Study 1 with visual perception of the same materials with respect to availability of different information from static and dynamic vision. In Study 3, we investigated how various hand constraints affect the perception of softness dimensions. In Study 4, we tested whether existing relationships between sensory and affective properties of materials are modifiable by learning.

In the first study, we focused whether EPs are adapted to both task and the material. We selected 19 materials and 15 adjectives which are associated with softness dimensions or roughness (i.e., control dimension) for the experiment. During the experiment, participants freely and actively explored and rated the materials (e.g., fluffiness) while we recorded their hand movements. These hand movements were decoded by categorizing into different EP groups. A linear support vector machine predicted material categories from our EPs successfully. Decoded hand movement data was analyzed using a multivariate analysis of variance (MANOVA). MANOVA results showed that EPs depended on the material category (e.g., for granular materials run through and rotate used frequently), the task (e.g., to judge the deformability of any material pressure was often applied), and the interaction between material category and task. For instance, pulling is used to judge deformability and viscosity of viscous materials, while it is used to judge deformability, but not viscosity of furry materials. Therefore, EPs are not only determined by material category or task but also their interaction. Together, the results support the idea of multiple perceived softness dimensions and further suggest that participants actively adapt their EPs in very differentiated ways for judging different softness dimensions in different material categories. The potential implication of these findings ranges from prosthetics to robotics wherever the understanding haptic perceptual spaces of different material qualities would help optimizing grasping and exploring abilities.

In Study 2 we investigated how perceived softness differ depending on static visual, dynamic visual, and haptic information. We conducted a behavioural experiment with two conditions: dynamic visual information, static visual information and compare the two conditions with the results from Study 1 (i.e., haptic judgements). Under two experimental conditions people explored and subsequently rated different attributes of everyday materials (e.g., hair gel). In static visual information condition, participants rated attributes of close-up images of the same materials we had in Study 1. In the dynamic visual information condition participants rated the same attributes after watching the videos we recorded in Study 1 — someone else haptically exploring soft and non-soft materials. Our results, replicating and extending previous results, have shown high perceptual correspondence between haptic, static, and dynamic visual conditions. Correspondence tended to be the strongest between haptic and dynamic visual conditions in most cases. Results are discussed in terms of availability of information through different senses or previous experience with the materials.

Although typical interaction of humans with the objects result in bare hand interactions sometimes bare-hand explorations is not preferred or not possible. For instance, wearing protective gloves for work or combined sensor gloves in mixed reality experiments. In Study 3, we tested how different haptic restrictions affect perceived softness. We targeted softness because, as discussed before, softness makes use of both tactile and kinesthetic information and it might be highly sensitive to restrictions. To this end, we run a within-subjects experiment with four different conditions which are bare hand, open-fingered glove, open-fingered glove with rigid sensors, and full glove. Participants freely and manually explored and rated 10 materials on 15 sensory adjectives. The materials and adjectives were selected from Study 1 to represent extreme values on different softness dimensions. First of all, we analyzed the consistency across participants by calculating pair-wise correlations between each participant with the remaining participants for each condition. We performed PCA on ratings of each constrain condition separately. Then, using factor values we calculated Procrustes distances between each perceptual space (i.e., perceptual spaces extracted from PCA of perceptual responses of each condition). Distances between perceptual spaces were low that we were able to perform a combined PCA across perceptual spaces which would allow us to assess fine-grained differences/similarities across constrain conditions. We extracted three dimensions from the combined PCA which are *granularity*, *viscosity*, and *surface softness*. Overall, PCA, Procrustes, and correlation analyses showed that softness perception is highly similar across constraint conditions. However, on a more detailed level (i.e., material-adjective combination), we found that glove condition differed from the others specifically for the judgements on surface softness. Therefore, perceiving surface softness might require information from specifically the fingertips which can be reduced by covering the fingertips. This is sensible considering increased number of mechanoreceptors in distal phalanx compared to distal and middle phalanx (Johansson & Vallbo, 1978)

So far, all three studies focused on the sensory properties of the materials. In Study 4, we addressed to the affective properties of material. We were interested how much existing relationships between those properties can be manipulated. To this end, we testes unlearning of previously observed negative relationship between roughness and valence and positive relationship between granularity and valence. The experiment had two phases: learning and experimental phase. In the learning phase, participants explored materials which are fine-grained (e.g., sand) or rough (e.g., bark) when they simultaneously observed negative and positive images from the International Affective Picture System (IAPS, images selected based on valence and arousal values). In other words, granular materials matched with negative images and rough materials matched with positive images. Whereas the control group has interacted with materials from different material categories. In the experimental phase, all participants explored a very diverse set of 28 materials and rated based on twelve affective adjectives. We found a significantly weaker relationship between valence and granularity in the experimental group compared to the control group, while roughness-valence relationships did not statistically differ across groups. In other words, valence of granular materials is unlearned but not rough materials. We attributed this differences in strength of the relationships to the distinction between learned and hard-wired connections.

2. Task and material properties interactively affect softness explorations along different dimensions

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Haptic research has frequently equated softness with the compliance of elastic objects. However, in a recent study we have suggested that compliance is not the only perceived material dimension underlying what is commonly called softness (Dovencioglu et al., 2021). Here, we investigate whether the different perceptual dimensions of softness affect how materials are haptically explored. Specifically, we tested whether also the task, i.e., the attribute that a material is being judged on, might affect how a material is explored. To this end we selected 15 adjectives and 19 materials that each associate with different softness dimensions for the study. In the experiment, while participants freely explored and rated the materials, we recorded their hand movements. These movements were subsequently categorized into distinct exploratory procedures (EPs) and analyzed in a multivariate analysis of variance (MANOVA). The results of this analysis suggest that the pattern of EPs depended not only on the material's softness dimension and the task (i.e., what attributes were rated), but also on an interaction between the two factors. Taken together, our findings support the notion of multiple perceptual dimensions of softness and suggest that participants actively adapt their EPs in a nuanced way when judging a particular softness dimensions for a given material.

2.1. Introduction

Haptic perception factor into many decisions we are facing in daily life. For example, the feel of an object matters when deciding whether the mango is ripe, or whether the chair is comfortable enough to sit on. While the tactual impressions of objects can vary greatly, researchers have shown that these can be characterized by only five main dimensions: warmness (cold/warm), hardness (hard/ soft), micro and macro roughness, and friction (moistness/dryness, stickiness/slipperiness) (Okamoto et al., 2013), with softness being one of the most investigated dimensions.

Previous studies on haptic softness typically think of compliance as the physical correlate of softness (Okamoto et al., 2013; Higashi et al., 2019; Cellini et al., 2013; Bergman-Tiest & Kappers, 2009; Xu et al., 2019), which is measured as the deformation of an elastic object in response to an applied force (Di Luca, 2014, Zöller et al., 2019; Kaim & Drewing, 2011) (see (Higashi et al., 2018) for an exception). In contrast, everyday experiences of soft materials seem to include a much broader range of physical correlates: from squeezing playdough to stroking a rabbit's fur to digging your fingers into the warm sand on the beach. In previous work, we formally followed up on this observation in an experiment were participants haptically explored and rated a wide range of soft (and non-soft) materials. Analyzing the data with the Principal Component Analysis (PCA), we discovered that perceived softness not only covaries with the compliance of the material but also with its viscosity, granularity, and furriness (Dovencioglu et al., 2021). The idea of a multidimensional construct 'softness' would be consistent with previous work (Dovencioglu et al, 2021; Di Luca,2014; Caldiran et al., 2019; Klatzky, 2019; Jones, 2019). But do these softness dimensions also affect how we explore materials? To answer this question, it is necessary to allow participants to freely explore the stimuli in a study, since active haptic exploration of surfaces and objects provides important information that can hardly be achieved from other senses (Klatzky et al., 1985; Klatzky & Lederman, 1999), or passive interactions.

While actively exploring objects and materials, humans use a set of stereotypical movement patterns to perceive different dimensions (Gibson, 1962; Lederman & Klatzky, 1987; Lederman & Klatzky, 1990; Higashi et al., 2018]. For instance, in order to perceive texture, a repetitive lateral motion is typically generated, or for temperature, stationary contact is used in order to maximize the contact area between object and skin. Individual exploratory procedures are also known to be associated with the perception of specific dimensions. For example, during

Table 2.1. Exploratory procedures observed in Dovencioglu et al. (2021) and in the present study.

EP name and example	Definition of the EP	EP name and example	Definition of the EP
 Pressure	Applying normal force to squeeze a material between palm and fingers or using one or more fingers to apply normal force (similar to pressure in [17-18]).	 Stroking	Moving the fingers or the whole hand laterally across objects to get information about the surface while applying only gentle force (not strong enough to deform an object). If the thumb is used it is considered rubbing (rubbing and stroking are linked to lateral motion in [17]).
 Stirring	Immersing one or more fingers into a material and moving its particles (this can be rotational).	 Running through	Picking up some parts/portions of a material and letting them trickle through the fingers.
 Rubbing	Applying torque or lateral force with varied pressure levels, sometimes sweeping a material between index and thumb fingers or forcefully stroking the material with the tumb while balancing an object with the other fingers.	 Rotating	Lifting portions of a material to move and turn its boundaries typically inside the finger(tip)s.
 Pulling	Stretching part of a material by moving fingers or seperating them from each other.	 Tapping	Repeatedly and rapidly hitting a material with knuckles, fingertips [4-5], or nails.
 Flat-handed pick up	Trying to lift up a portion of a material by maximizing the contact surface with the flat hand.		

First 8 definitions adapted from (Dovencioglu et al.,2021), 'flat-handed pick up' obtained from the present study.

softness (compliance) judgements *pressure* is usually used, which involves squeezing an object between index finger and thumb or pressing the object with a single finger (Lederman & Klatzky; 1987; Lederman & Klatzky, 1990). While *pressure* might be optimal for exploring an object's compliance (Lederman & Klatzky, 1993), we have recently shown that humans use, in fact, several additional exploratory movements (Niess, 2018; Dovencioglu et al., 2021), each being associated with a particular type of material. Table 1 shows examples of these exploratory procedures (Lederman & Klatzky, 1993; Neiss, 2018; Dovencioglu et al., 2021) for a range of soft and non-soft materials.

In addition to the material properties, i.e., whether a material is granular or furry, previous work has shown that EPs are also influenced by the aim of exploration, i.e., the specific perceptual task (Callier et al., 2015), and a recent study on texture exploration even suggests that both, the perceptual task *and* the surface properties affect exploratory movements when exploring with a single digit (Callier et al., 2015).

Here we ask whether a similar combined effect of task and material on exploratory movements exists, when participants judge different aspects of softness of every-day materials. To address this question, we employ a large range of soft and non-soft materials in a free exploration paradigm. The experiment builds on our previous work (Neiss, 2018; Dovencioglu et al., 2021) which shows, that perceptual dimensions of softness influence EP patterns. Specifically, we use adjectives and materials that each tap predominantly into one specific perceptual dimension of softness. We verify our selection with a PCA before investigating with a MANOVA the potential effects of- and interactions between the task and material properties on EP patterns.

2.2. Methods

2.2.1. Participants

30 students (aged 18-38 years; average 23.6 years, 21 women, all right-handed) from Giessen University participated in the study and were compensated with 8 €/hour for their time. All participants were naïve to the purpose of the study and spoke German at a native speaker level. None of them reported sensory, motor, or cutaneous impairments. The two-point discrimination threshold at the index finger of the right (dominant) hand of all participants was 3 mm or better. The study was ethically approved by LEK FB 06 in accordance with the declaration of Helsinki (2008). Participant gave written informed consent.

2.2.2. Setups, materials, and adjectives

Active noise canceling headphones (Sennheiser HD 4.50 BTNC) were used to eliminate any sounds that might have been caused by the exploration of materials, and to present beeps that signaled the start and end of the exploration period. The experiment was programmed in MATLAB 2017a (MathWorks Inc., 2007) using Psychtoolbox routines (Brainard, 1997; Kleiner et al., 2007). A standard laptop was placed to the left of the participants to run the experiment and to collect rating responses. During the experiment hand movements were recorded with two identical Sony Digital 4K Video Cameras (recording 28-bit videos at a spatial resolution of 1920 × 1080 pixels). Cameras were placed on tripods to the left and right across the table from the observer (see Figure 2.1. for a typical view).

During the experiment, participants were seated in front of a table. A horizontally rotatable armrest on this table, ensured that all participants explored the materials from the same distance and position and also reduced potential strain on the arm. A green curtain hid the materials from the participant's view. The experimenter sat behind the curtain and placed plates (diameter 21.5 cm: Figure 2.1) that held the materials on the table. Materials that would be substantially altered through exploration (e.g., hand cream) were renewed for each participant. Table II shows the 19 materials that we selected according to material categories (*deformable, fluid, hairy, granular, rough*) that were derived via PCA in earlier work (Dovencioglu et al., 2021), as well as a control condition. For the present study, we wanted to employ only materials that were highly representative of a given perceptual dimension, i.e., those which loaded with an absolute value of 1.5 or larger (which corresponds to 1.5 standard deviation in the z-standard values). An additional selection criterion for materials in one dimension was that they did not have additional high loadings on any of the other dimensions. For each material dimension, we chose 3 materials: two positively and one negatively loaded (indicated by the (+), and (-), respectively in Table I. If no negative loaded material existed, we picked only two positively loaded exemplars. For the roughness dimension we also included sandpaper, as this is a prototypical rough material.

Materials for the control category included those that showed high loadings on more than one dimension in (Dovencioglu et al., 2021), like paper balls, linen and sponge.

Figure 2.1. Setup and example material used in the experiment.

15 sensory adjectives were selected based on their component scores on deformability, viscosity, furriness, granularity (softness dimensions) as well as roughness (control condition) based on results by (Cavdan et al., 2019; Dovencioglu et al, 2021). Specifically, for each dimension we choose the two adjectives with the highest positive, and one with the highest negative load. If adjectives with high negative loads were lacking, we used three positively loading adjectives (e.g., granularity: sandy, powdery, granular, fluidity: moist, gooey, sticky; hairiness: velvety, hairy, fluffy). For roughness, there was only one positive and one negative adjective that loaded high: rough and smooth. All adjectives were translated from Turkish (Dovencioglu et al., 2021) into German. Both the German version and the English translation of all adjectives can be found in Table. III. Note, that we used the adjective wobbly instead of gooey because it better captured the property that we intended to convey in the German translation.

2.2.3. Design and Procedure

After giving written informed consent, participants completed a questionnaire that assessed any potential sensory, motor, or cutaneous impairments, as well as a two-point discrimination threshold determination task at the dominant hand's index finger. After this, participants were allowed three practice trials in order to get familiarized with the setup and the experiment. During the practice trial, participants rated a wood block on how *woody*, *gracile*, and *structured* it felt to them.

During the experiment each participant rated 15 sensory adjectives for each of the 19 materials. Specifically, they indicated the extent (Likert item 1-5) to which they think an adjective applied to a material: 1 indicated '*not applicable*' and 5 '*applies strongly*'.

Table 2.2. Materials selected for the experiment and their associated dimensions.

Deformability	playdough (+), stress balls (+), stone (-);
Viscosity	hand cream (+) and hair gel (+);
Furriness	fur (+), velvet (+)
Granularity	sand (+) and salt (+)
Roughness	sandpaper (+), felt (+), aluminum foil (-)
Control	paper balls, wool, linen, lentils, cranberries sponge, cotton balls

Note that sugar was used in (Dovencioglu et al., 2021). However, we replaced it in our study with salt in order to avoid the increasing stickiness of sugar in time after exposure.

On each trial, participants first saw an adjective on the laptop screen. In order to indicate that they were ready to start the exploration of the material they had to press the space button with their left hand. Then, a beep marked the start of the 4-second exploration time, and participants freely explored materials with their right hand. After 4 seconds a second beep signaled the end of the exploration time. Participants were instructed to disengage the exploration when the beep occurs by using the armrest to rotate their hand slightly to the left side (i.e., towards them), and to then indicate their rating of the material by pressing a button on the numpad with the left hand. The procedure of exploring a material and subsequently rating it was repeated 285 times (19 materials x 15 adjectives). Note, that all adjectives were rated independently and in random order during separate explorations. The presentation order of materials was also randomized in order to rule out systematic carry over effects. The experiment was self-paced, participants pressed the space button whenever they felt ready to proceed to the next trial, which usually happened after a couple of seconds. After the end of the adjective list, the experimenter changed the material.

Participants were encouraged to take breaks between materials and allowed to pull their hands back after every trial if needed. However, they were required to do so in order to clean their hand after touching certain materials (e.g., hair gel, sand, hand cream, etc.). The experiment took participants about1.5 hours (+/-20min, depending on individual speed and break durations).

2.3. Results

2.3.1. PCA on adjectives

We first calculated Cronbach's alpha between participants for each single adjective across materials in order to estimate the participants' consistency. Standardized Cronbach's α (Gliem & Gliem, 2003) revealed an excellent consistency between participants' ratings for each adjective (each $\alpha \geq .95$). Also, correlations r between participants' ratings for each material and adjective pair (see Figure 2.2) were high and statistically significant and ranged between .45 and .82 (p <.01.). This degree of consistency is in line with previous studies on sensory ratings (Schmid & Doerschner, 2018; Drewing et al., 2018).

After this, we averaged responses across participants for each adjective and material and submitted the averages to a covariance based PCA in order to verify the different softness dimensions that we found in earlier work (Dovencioglu et al., 2021). Prior to the PCA we used Bartlett's test of sphericity and the Keyser-Meyer-Olkin (KMO) criterion to assess the suitability of the data for this type of analysis. The KMO criterion of sampling adequacy yielded a score of .48, which is a borderline value. However, Bartlett's test of sphericity was significant, $\chi 2\ (105) = 415.79$, $p < .001$, which suggests that the observed correlations were indeed meaningful. The principal components were extracted according to the Kaiser-criterion and rotated using the varimax method.

Five principal components were extracted, explaining 94.3% of the variance (see Figure 2.3 for Scree plot). The first rotated component accounted for 25.9 % of the variance. It appeared to be related to the material's furriness or fibrousness because adjectives like fluffy, velvety, hairy,

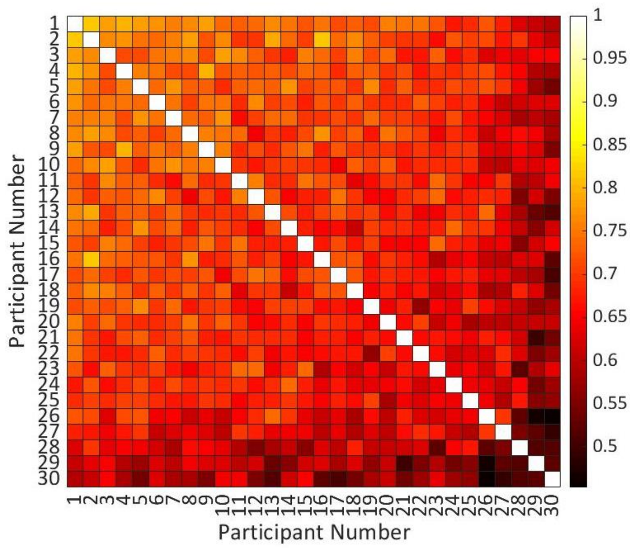

Figure 2.2. Pearson's correlation coefficient *r* for inter-participant correlations (i.e., correlations between each participant and all other participants). Higher correlations plotted in light colors (i.e., white) and lower correlations are plotted in darker colors (i.e., black). The heatmap is ordered by the average correlation per participant.

and soft loaded high on this component. The second component accounted for 20.6% of the variance in the data. We labeled this component viscosity because sticky, moist, and wobbly were high loading adjectives. Component three explained 20.6% of the variance. High loading adjectives on this component were powdery, sandy, and granular. Thus, we labeled it granularity. The fourth component explained 17.8% of the variance, with high loadings of the adjectives inflexible (- = negative load), elastic, and hard (-). Therefore, this component might be linked to deformability. Finally, the fifth component explained 9.4% of the variance, with high loadings of

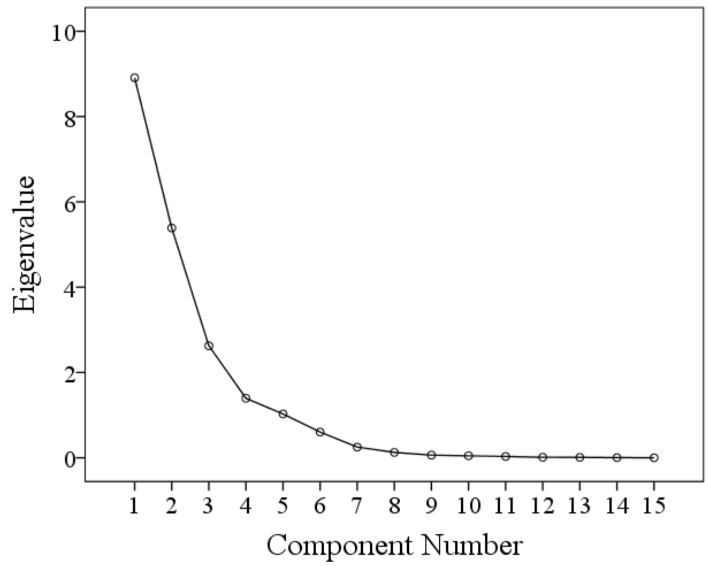

Figure 2.3. Scree plot for PCA of sensory adjectives. It shows that 5 components account for 94.3 percent of the variance.

the adjectives smooth (-) and rough, and consequently we labeled it roughness. These five components (4 dimensions of softness and one control dimension) confirm that the adjectives used in our study adequately tap into expected dimensions of softness. Inspecting the materials' component scores (Table 2.4.) confirmed that also the selected stimuli adequately represent the 4 dimensions of softness & roughness–and in overall agreement with our previous work (Dovencioglu et al., 2021) (cf. Table 2.2.). Note, that material categories in the following analyses are based on the scores from Table IV.

Table 2.3. Rotated component loadings of adjectives from Cavdan et al. (2019).

Adjective (English/ German)	Component I-V: Loadings				
	I. Furriness	**II. Viscosity**	**III. Granularity**	**IV. Deformability**	**V. Roughness**
Fluffy / flauschig	1.32	-0.41	-0.27	-0.28	0.16
Hairy / haarig	1.05	-0.25	-0.39	0.06	0.48
Soft / weich	0.90	0.36	-0.08	-0.68	-0.13
Velvety / samtig	0.80	-0.18	0.01	-0.32	-0.15
Moist / feucht	-0.12	1.14	-0.03	0.05	-0.25
Sticky / klebrig	-0.26	1.11	0.04	-0.15	-0.09
Wobbly / wabbelig	-0.03	0.95	-0.22	-0.39	-0.05
Sandy / sandig	-0.15	-0.12	1.14	0.29	0.26
Granular / körnig	-0.42	-0.03	1.08	0.69	0.24
Powdery / pulverig	-0.05	-0.05	0.97	0.17	0.10
Hard / hart	-0.61	-0.41	0.16	-0.90	0.10
Inflexible / unbiegsam	-0.23	0.07	0.42	-0.87	-0.05
Elastic / elastisch	0.11	0.27	-0.31	0.78	0.08
Smooth / glatt	-0.27	0.11	-0.20	0.11	-0.95
Rough / rau	-0.38	-0.33	0.37	0.13	0.70

Grayed-out adjectives are the highly loading adjectives per category, which will be used to calculate task dimension scores of the EPs (e.g., fluffy, hairy, soft, and velvety will be averaged for the furriness dimension) in the following analyses.

Table 2.4. Rotated component scores of the materials.

Material	Components				
	Furriness	**Viscosity**	**Granularity**	**Deformability**	**Roughness**
Fur	**1.99**	-0.12	-0.56	-0.38	0.66
Cotton balls	**1.47**	-0.42	-0.28	0.37	-0.02
Velvet	**1.05**	-0.9	0.25	0.95	-1.64
Wool	**1.4**	-0.13	-0.51	-0.15	**1.27**
Paper balls	-1.15	-0.9	-0.76	0.3	-0.09
Hand cream	0.09	**2.22**	-0.43	-0.37	-0.94
Hair gel	0.1	**2.18**	-0.45	-0.37	-0.8
Stress balls	-0.7	**1.27**	-0.17	**1.25**	0.37
Salt	0.04	-0.25	**2.67**	0.12	0.12
Sand	-0.01	0.15	**2.63**	-0.28	0.52
Stone	-0.74	-0.54	-0.67	-2.42	-0.55
Lentil	-0.23	-0.37	0.59	-2.1	-1.59
Sponge	-0.38	-0.63	-0.17	**1.33**	-0.15
Playdough	-0.78	0.17	-0.24	**0.96**	-0.6
Linen	0.37	-0.77	-0.11	0.86	-0.68
Sandpaper	-1.53	-0.63	-0.26	-0.58	**2.14**
Aluminum foil	-1.31	-1.11	-0.73	0.53	-0.78
Cranberries	-0.68	**1.24**	0.07	0.48	**1.37**
Felt	0.51	-0.44	-0.87	-0.49	**1.16**

Larger fonts indicate high loads (absolute value > 1, which corresponds to one standard deviation in the z-standardized values). Bold fonts indicate the high ***positive*** *loads that define the associations with material categories. Only for playdough the defining load marginally failed to exceed 1. Materials in italics load highly positive in two components.*

2.3.2. Hand movements

We next analyzed the video recordings of participants' hand movements during the exploration periods. Exploratory procedures were classified according to the list of eight EPs proposed in (Lederman & Klatzky, 1987; Dovencioglu et al., 2021) (see Table 2.1. for a detailed description). We also observed one additional hand movement: a "flat-handed pick up" resulting in a total of 9 possible EPs. For each 4-second exploration per individual, material and adjective we coded the frequency of occurrence of each of the 9 EPs, disregarding their duration. These frequencies were normalized to a "percentage value" by dividing 100% by the number of EPs observed in that trial (e.g., if 3 EPs were coded in a trial, each of the three EPs obtained a value of 33.3%).

Due to the extensive amount of labor when manually coding these videos only one rater coded all of the data, which was then used in subsequent analyses. In addition, two raters coded independently the same 50% of all videos (corresponding to 15 participants) in order for us to assess inter-rater reliability (Wray et al., 2017; Akbiyik et al., 2018). This was generally high (Cronbach's α = .89, p<. 001), corroborating the main coder's results. Prior to coding the movies, all raters had received training on the EPs. Specifically, they were given detailed explanations on the EPs, and they had practiced coding data from a pilot experiment. These codings were evaluated and compared, and disagreements between raters resolved by discussions. For example, we explained that hand motions that were generated by attempts to clean the hands-off parts of the materials (e.g., sand, playdough) were not to be counted as EPs. When discriminating between the different EPs raters were encouraged to focus on hand movements alone. For example, when differentiating between *pulling* and *pressure*, raters primarily relied on the positioning and movements of the individual fingers. This is a reasonable strategy, since finger dynamics can provide cues about the magnitude and the direction of the applied force: e.g., in *pressure* two fingers approach each other and force is applied towards the object. In contrast, in a typical *pulling* motion two fingers touch and then move apart, indicating that forces direct away from the object. Another example is the distinction of *rotate* from *rubbing* when coding the hand movements for granular materials. Here, raters focused primarily on the motion trajectory, the applied force, and the sliding velocity in order to differentiate these two EPs. An EP was classified as *rotate* when the motion trajectory was circular, and the sliding velocity and the applied force appeared relatively low. On the other hand, when the motion trajectory was rather lateral, and the sliding velocity and applied force appeared high, the EP was classified as *rubbing*.

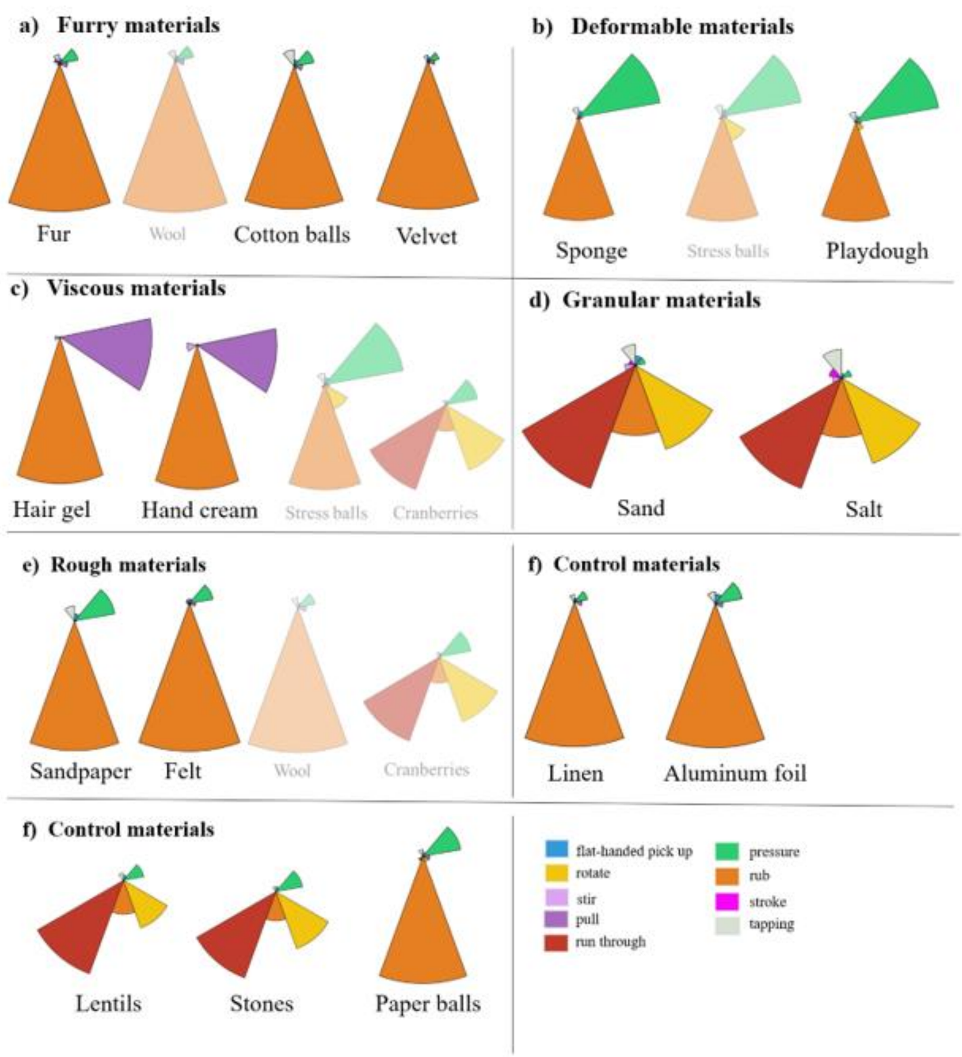

Figure 2.4. Mean frequency of occurrence of each EP as a function of material category: *furry* (a), *deformable* (b), *viscous* (c), *granular* (d), *rough* (e), and *control* (f). Individual materials with transparent diagrams loaded high on more than one dimension.

2.3.3. Effects of Task dimension and Material on EPs

After establishing that our choice of rating adjectives and materials adequately represent specific perceptual dimensions of softness (and roughness, as a control dimension), we conducted two-way repeated-measures MANOVAs in order to investigate the individual and combined effects of material properties and task dimension on the patterns of exploratory procedures. To this end, we collapsed the individual frequencies of all EPs across the adjectives that load highest on

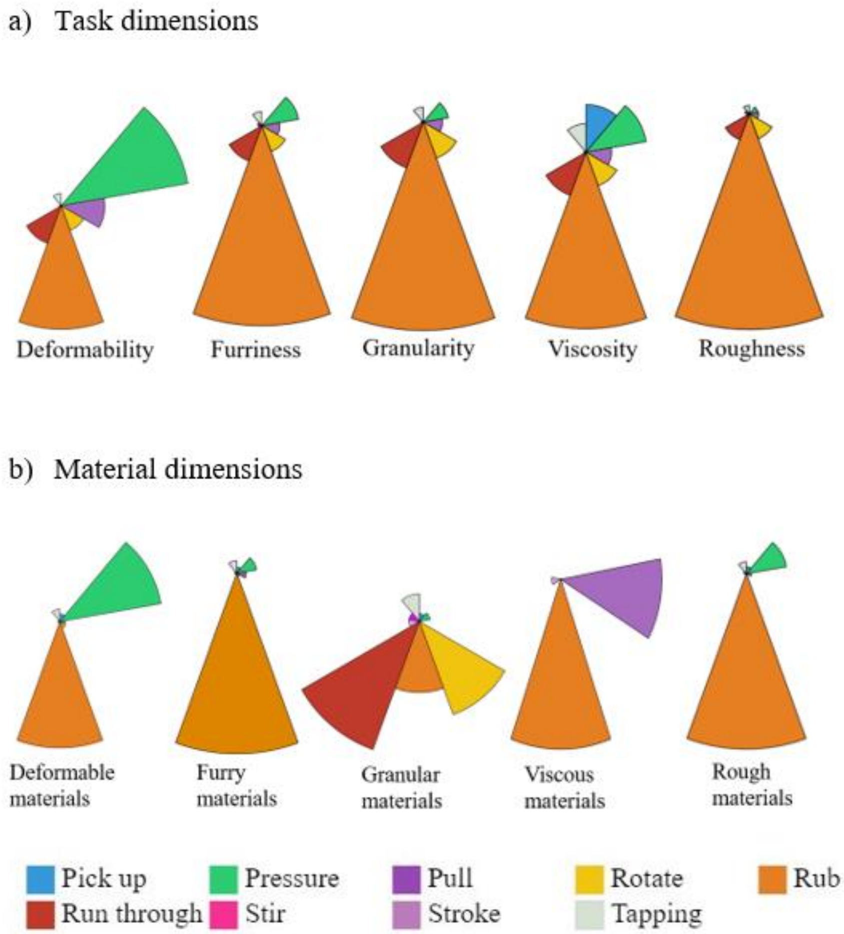

Figure 2.5. Mean frequency of occurrence of each EP as a function of task (a), and as a function of material dimension (b).

each of the four different perceptual dimensions and roughness, separately for each material. Specifically, we collapsed EP frequencies for ratings of fluffy, hairy, soft, and velvety for the *furriness dimension*; moist, sticky, and wobbly for *viscosity*; granular, powdery, and sandy for *granularity*; hard, inflexible, and elastic for *deformability*; and smooth and rough for *roughness*. The dependent variables in this MANOVA were the EP frequencies for *flat handed pick up, pressure, pull, rotate, rubbing, run through, stir, stroke,* and *tapping*.

We conducted the first MANOVA with the independent variables of task dimension (5 levels) and individual material (19 levels) in order to test for general effects of *material*. The MANOVA yielded significant main effects of individual material, $V = 2.78$, $F(162, 4698) = 12.99$, $p<.01$, partial $\eta^2 = .31$, and task dimension, $V = 2.23$, $F(36, 444) = 15.59$ $p<.01$, partial $\eta^2 = .56$, using Pillai's trace (Figure 2.4 and Figure 2.5a, these plots use the area of circle segments to convey the relative EP frequencies percentages. All segments add up to 100% in total). The interaction between material and task dimension was also statistically significant, $V = 1.13$, $F(648, 18792) = 4.18$, $p<.01$, partial $\eta^2 = .13$.

In order to also check for homogenous effects of material type, we conducted a second MANOVA. We organized our 19 materials into separate categories; we agglomerated those that loaded high on the same softness dimension (Table 2.3.). Materials that loaded high on two different dimensions (Table 2.4, italics) were excluded from this analysis. We then investigated how EPs were influenced by both the particular *category* of a given material and the *task dimension* (5 levels). EP frequencies were averaged over each *material category* (*furry, viscous, granular, deformable, and rough [control category]*) and *task dimension* (*furriness, viscosity, granularity, deformability, and roughness [perceptual control dimension])*. As before, the dependent variables were the frequencies of the nine EPs. The (5x5) repeated-measures MANOVA yielded significant main effects of *material category*, $V = 2.45$, $F(36, 444) = 19.5$, partial $\eta^2 = .61$, and *task dimension*, $V = 1.98$, $F(36, 444) = 12.06$ partial $\eta^2 = .49$, as well as a significant interaction between both, $V = 1.67$, $F(144, 4176) = 6.61$, partial $\eta^2 = .19$ (all $p<.01$, using Pillai's trace, Figure 2.6).

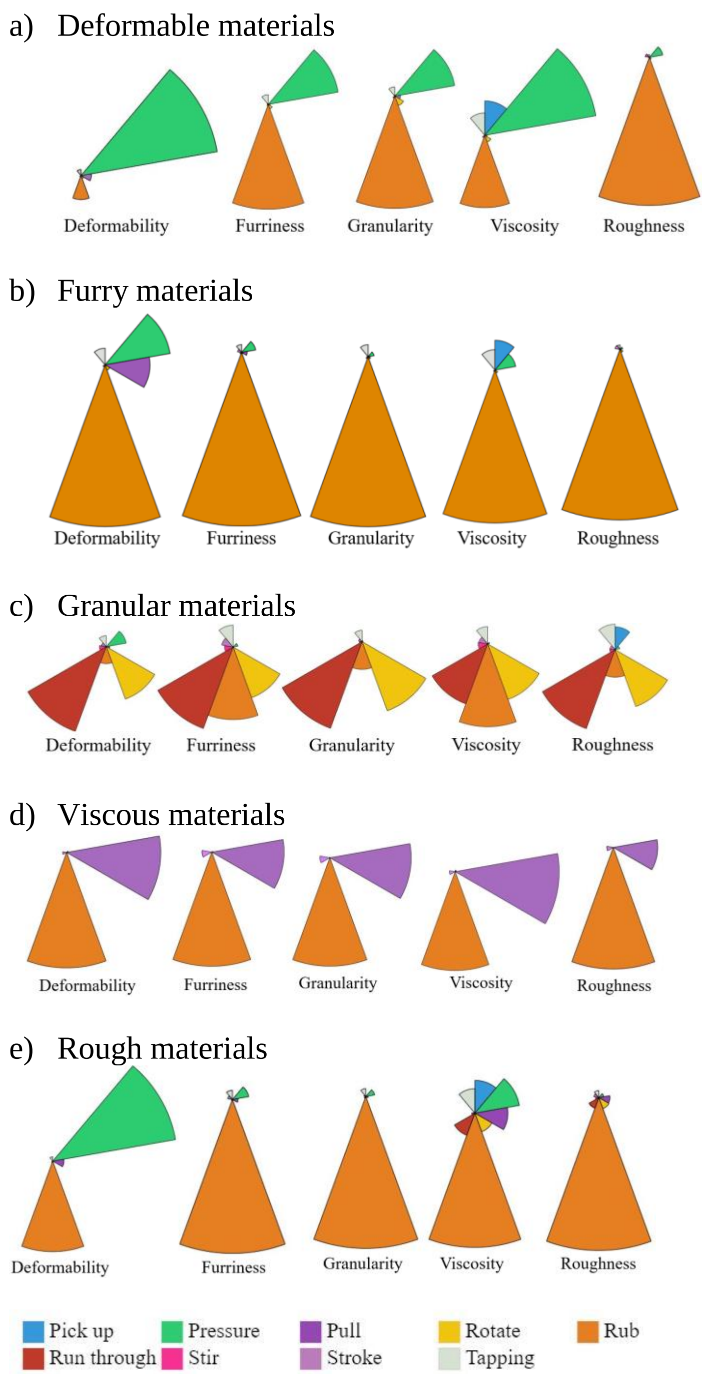

Figure 2.6. Mean frequency of each EP as a function of task for different material categories: *deformable* (a), *furry* (b), *granular* (c), *viscous* (d), and *rough* (e).

To investigate the contribution of each dependent variable to the model we conducted follow-up univariate repeated-measures ANOVAs for each EP. The results indicate that the frequency of EP occurrence differed significantly across *material categories* for flat handed pick up, pressure, pull, rotate, rubbing, run through, stroke, stir and tapping (Table 2.5.). Univariate ANOVAs for each EP showed that most EP frequencies varied significantly also across *task dimensions* for flat handed pick up, pressure, pull, rotate, rubbing, run through, stroke, and tapping, but not for stir (Table V). Following up the interactions with individual ANOVAs we found the

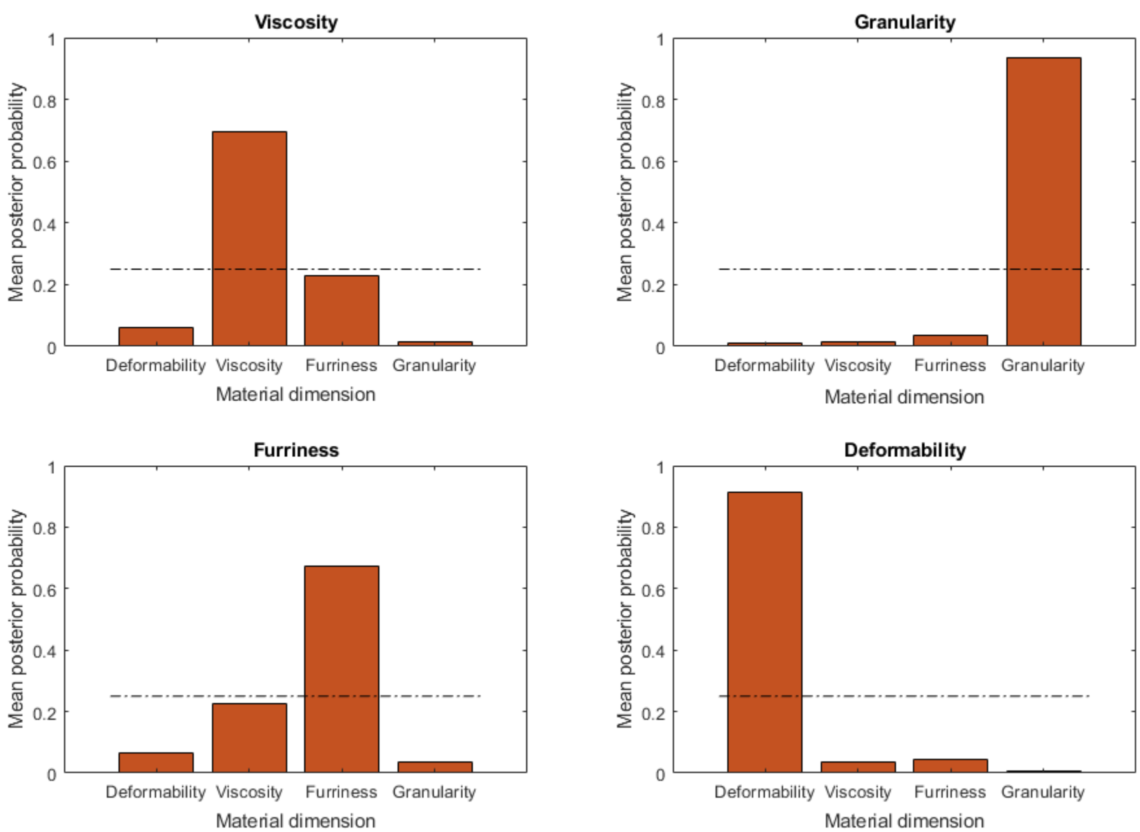

Figure 2.7. The performance of a linear support vector machine predicting softness dimensions of the materials from the EP frequencies. Specifically, we plot the mean posterior probability for each material dimensions. The dashed line indicates the chance level (25%).

following EPs significant: flat handed pick up, pressure, pull, rotate, rubbing, and run through. Interactions were not significant for stroke, stir, and tapping (Table 2.5.).

2.3.4. Predicting the material category from EP patterns

The analyses above and Figures 2.4 & 2.5 suggest that EPs change as a function of *material category* and the *task dimension*. Next, we wanted to determine whether EP patterns can be used to predict the perceived material categories. To do this, we used a machine learning approach and trained a support vector machine (SVM, with Euclidian distance as error metric) on 90% of the EP data (540 of 600 observations [30 participants x 5 tasks x 4 material categories], 135 per material category [related to salient softness dimension: *viscosity, granularity, furriness, and deformability*]) using the built-in Matlab function *fitcecoc* with a ten-fold cross validation (*crossval* function Matlab). We determined the optimal size of the training data by finding the best parameters to create a hyperplane which divides the data into four categories using a Gaussian kernel. Also, ten-fold cross-validation prevents overfitting and provides a generalized classification error. The goal of the SVM was to predict the perceived material categories of the remaining data (60 observations). Figure 2.7 shows that prediction performance of the SVM was overall very high (86.67%), with best classification for granularity (94%), followed by deformability (92%), viscosity (73%) and furriness (71%). Classification performance was significantly above the chance level (25%) in all conditions.

2.4. Discussion

Correctly judging the softness of objects enables us to make critical decisions, such as whether a surface is safe enough to sit on or whether food is edible. We have shown here that, unlike previously thought, soft materials are not just explored by applying pressure, but by using a number of different exploratory procedures. We also found that participants actively adapt how they use these EPs as a function of the perceptual task. Both findings challenge the existing concept of softness as a single dimension. Moreover, interactive effects of task and material category on EP patterns, suggest a very fine-tuned usage of hand movements, which goes beyond the idea that

EPs are movement schemes that are closely and heuristically linked exclusively to the task (Lederman & Klatzky, 1987).

Some of the results may seem surprising since they go beyond what one's intuition would predict from the daily interactions we have with soft materials. For instance, intuitively, one would think that people primarily stir viscous materials, yet we found that people instead tend to pull viscous substances. Another surprising finding is that participants tended to always rub materials – independent of what it is they are touching and what it is they are judging about a material. However, this EP is flexibly supplemented in different degrees by additional EPs, which are associated with specific material properties, the task, or an interaction of the two. So, instead of the strict specialization of a single movement, we see that people use combinations of movements (e.g., run through followed by rotate for granular materials), which might help them to gather an optimal set of information.

2.4.1. Influence of individual material properties and material categories on EPs

We found that EPs were affected by the individual material properties, which would be consistent with previous research on haptic softness and texture perception (Lederman & Klatzky, 1990; Callier et al., 2015). Many of these effects can be explained by the material category: EPs differed between individual materials if the materials loaded high on different softness dimensions. Therefore, we collapsed the data for individual materials that loaded high on a particular dimension. This yielded 5 material categories (4 soft & 1 rough). As can be seen from Figure 2.5b, the patterns of EP differed substantially between material categories. This is consistent with previous work (Nagano et al., 2014; Yokosaka et al., 2017) which suggested that perceptual dimensions, that are associated with specific material properties affect the way we explore them. We found the following associations for softness dimensions:

- The most frequently used EPs for highly granular materials (i.e., salt and sand) were *run through* and *rotate* (Figure 2.4, 2.5b). It could be that this combination of EPs is particular useful for granular materials: while *run through* might provide initial coarse information about the density, weight, or viscosity of the grains, rotate provides follow-up, refined information about the size or shape of individual grains. To test this idea, we performed a follow up analysis on the temporal sequence of EPs for granular materials. Briefly, one coder recoded hand movements of 10 random participants with respect to the time sequence of EPs for all granular materials (10 participants x 2 materials, sand & salt, x 15 adjectives = 300 trials), and we analyzed the frequency of combination of the first 2 EPs occurring in a trial—across all trials (with a chance level 1.4 %, for 72 ordered combinations of 9 EPs). Only 5 EP combinations were significantly more frequent than chance level (calculated for 300 observation using a Binomial distribution), and results support our idea, showing that the most frequent order of the first two EPs in a trial was indeed *run through-rotate* (56.3% of trials), followed with quite some distance by the ordered combinations *rub-run through* (10.0%), *rub-tapping* (4.3%), *rotate-rub* (3.67%), and *run through-rub* (3.3%).

- Participants tended to explore hair gel and hand cream, which are associated with viscosity, mostly by *pulling* in combination with *rubbing*. These two EPs may test complimentary aspects of highly viscous materials: *Rubbing* might provide information particular on stickiness/friction aspects (Hollins, 2006) while *pulling* might estimate tensile ductility.

- Participants frequently used *rubbing* for cotton balls or fur, which have large values on the furriness dimension. *Rubbing* is a lateral and forceful EP, and hence probably particularly useful to explore characteristics of deformable surface structures, i.e., furry surfaces.

- For sponge and playdough, materials that score high on the deformability dimension, participants used more frequently *pressure* than for other material categories. This fits with previous findings showing that pressure is used and well-suited to judge object compliance (Klatzky & Lederman, 1999; Klatzky & Lederman, 1990). In addition, *rubbing* is frequently used in deformable materials as it is the case for other material categories. We will discuss this point below.

- We also obtained typical uses of EPs for rough materials, namely a high frequency of *rubbing*. This is consistent with (Lederman & Klatzky, 1990) where the roughness-associated EP was *lateral motion*, which we here differentiated into *stroke* and *rubbing*.
- In line with previous work (Dovencioglu et al., 2021), *rubbing* was used frequently in most material categories: for *furry* materials (e.g., fur or cotton balls), for *viscous* materials (e.g., hand cream and hair gel), for *deformable* materials (e.g., playdough and sponge), for *rough* materials (sandpaper or fur). It was used less likely for *granular* materials (e.g., sand or salt). *Rubbing* may be particularly informative compared to other EPs because it can provide force and structural (micro-shape) information at the same time, which may not hold to the same extent for, e.g., stroke, pulling, pressure or tapping (Akbiyik et al., 2018). Thus, we speculate that participants might have frequently used this EP because it is highly informative in general.

A limitation of the current study might be that in a few selected cases, a specific EP might be hard to apply to some specific material (e.g., *running through* felt), or conversely a material may allow to apply only a few of the EPs defined in this study. Would this not imply that preferences (and consequently overall frequencies) for an EP might be overemphasized for certain materials? We argue that this argument would only apply if there was a finite fully described number of potential EPs that are possible. If that was the case, then the imposed limitations on the possible types of EP by the properties of the material would lead to an overestimation of the usage of the residual EPs in the set. However, human movement control is quite flexible and adaptive, and a manifold of different EPs is possible, and we did not claim that the list of our 9 EPs is an exhaustive one. Therefore, the baseline for any EP frequency estimate is the (infinite) number of theoretically possible EPs. For this reason, we believe that our interpretation of the results would not change if some of the 9 EPs were not "possible" for some of the materials in our study. Another limitation could be, that the raters' categorization of exploratory procedures might have been influenced by seeing the material. However, given that observers are able to recognize materials by only watching the point-light hand motions of others (Yokosaka et al., 2017), we believe that the dynamics of the fingers and hand alone might have provided raters with sufficient information to discriminate between different EPs. In a follow up study, we will test this idea formally.

2.4.2. Influence of task dimensions on EPs

EP frequencies also varied as a function of the task dimensions, i.e., which perceptual dimension was rated (Figure 5a). Specifically, and in line with (Lederman & Klatzky, 1990), judging roughness was primarily associated with a rubbing motion (would have been categorized as lateral motion in (Lederman & Klatzky, 1987)), whereas the deformability judgments were most frequently associated with applying pressure. The softness dimensions furriness and granularity were also mainly explored by rubbing, and to rate the viscosity of a material caused participants to both rub and apply pressure to the material, with lower frequencies in-between those for deformability on one side and furriness/granularity on the other side.

The perceptual task modified the usage frequency of EPs less than did the material category. However, we also saw that for each perceptual task not only one EP is dominant, but a number of additional different EPs could occur, potentially providing complementary information to inform the perceptual process. It is quite possible that the order of EPs matters when judging different properties of the materials. For example, it could be that for judging the deformability of a material that the first EP should always be an attempt to compress it, i.e., to apply *pressure*. We tested this idea by investigating whether there were any significant temporal relations between EPs when judging deformability. Specifically, we recoded hand movements of 10 randomly chosen participants with respect to the temporal occurrence of EPs for two representative materials of each material category (*furry*: fur and cotton balls; *granular*: sand and salt; *viscous*: hair gel and hand cream; *deformable*: sponge and playdough; *rough*: sandpaper and felt) and all judgments (3 adjectives) pertaining to the deformability of the material. Then, we analysed the frequency of EP-pairs occurring in a certain order for each of the 5 material categories (yielding 60 datapoints per material category). We considered ordered EP pairs that occurred significantly more often than chance (chance level 1.4 %, test calculated for 60 observation using a Binomial distribution) and tested for these whether the frequency of one order of the two involved EPs was significantly more frequent than that of the other order (calculated again for 60 observations using a Binomial distribution, using the smaller frequency as a baseline). We found significant temporal relationships between the first two EPs in the following cases: For deformable materials *pressure* was followed by *rub* in 25% of the trials (the other order *rub-pressure* was only observed in 5 % of trials); again, for granular materials *run through* was followed by *rotate* in 55% of the trials (vs. 6.67 % for *rotate-run through*); finally, for viscous materials *rub* was followed by *pull* in 33% of the trials (vs. 18.3 % for pull-rub). These findings support the idea that complementary information is gained successfully from different EPs, at least for some material categories. While the first EP may provide information on more general characteristics of the materials, the second EP may help people gain more detailed information. For example, for deformable materials a first coarser judgment of deformability by applying *pressure* might be fine-tuned by more careful rubbing of the materials between the fingers. However, for furry and rough materials, we did not find temporal relationships in EPs. But this does not render the secondary EPs useless. Regardless of a sequence, using an additional EP is likely still enhancing the information gain, and we plan to test this formally in future work.

2.4.3. Interactions

Our results show that the material category effects explained more of the total variance in the EP patterns than the task dimensions. However, we also found an interaction between these two factors (subsection D in results). This implies that different combinations of these two factors affected EP frequency differently. This is illustrated in Figure 2.6: for granular materials run through and rotate were used with high frequencies across task dimensions, however, the exact frequency of these EPs and the frequency of additional EPs varied with the task dimension: for example, while judging the viscosity of granular materials participants used less run through and more rubbing compared to other task dimensions. For other material categories rotate and run through were hardly used for any task. In fact, a similar variation across task dimensions was not observed for any other material category. This result suggests that EPs are not determined by task or material in isolation, but that instead participants tended to explore materials with a particular set of EPs in order to optimize information apprehension (Lederman & Klatzky, 1990). Specifically, we find in this study that the interaction of task dimension and material category might influence such an optimization process. We next highlight a few noteworthy interaction effects between the material category and the task dimension (Figure 2.6):

- Overall, people frequently use the EP *pull* for viscous materials (Dovencioglu et al., 2021). *Pulling* is used in similar frequency to judge deformability and viscosity of viscous materials, whereas for furry materials it is used to judge deformability, but not viscosity. This may relate to different effects and information gains in viscous vs. furry materials: By *pulling* the fingers apart in viscous materials participants may try to understand primarily the tensile ductility, which contributes both to deformability and viscosity judgments. However, in furry materials they may mainly gain information on the bending characteristics of textural elements, which is relevant for deformability but less so for viscosity judgments.

- *Pressure* is used across materials and tasks. However, the proportion of applied *pressure* changed across material and task dimension combinations. For example, for deformable, furry or rough materials, it is more frequently used for the deformability tasks than for other tasks, which is not true for granular and viscous materials where it is hardly used at all. This likely reflects that the normal forces that are applied during pressure are quite useful to judge deformation of deformable, rough, and (less so) furry materials, but for granular and viscous materials applying force in varying directions may provide better information.

- While exploring furry or viscous materials people frequently use *rubbing* for any task dimension, whereas its usage depends clearly on the task for rough, deformable and granular materials, e.g., it is used less for deformability judgments as compared to other judgments. This might be the case because deformability judgments in the former, but not in the latter type of materials can be informed by lateral movements during *rubbing*.

- *Rotate* is mainly used for granular materials and hardly for other material categories. Still, for granular materials people adapt the usage of the EP to the task dimension. It is most likely used when the task is to judge granularity and less for furriness, roughness or deformability tasks. Probably, rotation is particularly useful for granularity judgments here, because it gives information about shape and size of grains.

- *Run though* is only used for granular materials, because physically it is not possible to apply this movement to materials that do not have grains. Again, the frequency of the usage is modulated by the task. In particular people applied run through less to granular materials when they judged viscosity as compared to other dimensions. Probably, viscosity judgments manly concern the behavior of the whole material rather than the (sum of) individual behavior of grains. Overall, *run through* and *rotate* seem to be highly specialized EPs in order to gather information about granular materials, and the frequency of using these EPs is further modulated by the task dimension.

Flat-handed pick up is hardly ever used across material categories and task dimensions except for one specific case. When the task is to judge viscosity, it is used in different frequencies for different material categories. People used it for deformable, furry, and rough materials but hardly for viscous materials—maybe because for viscous materials its special functions are already appropriately fulfilled by the EP of *pulling*. Overall, our results show that participants show differentiated patterns of EPs as a function of task dimension as well as of the softness dimension associated with a particular material. This further supports the idea that multiple perceptual dimensions of softness exist. However, how can we ascertain that the observed dimensions are indeed essentially related to perceived softness: In daily life, we often judge the softness of quite diverse materials to guide important decisions about how we should interact with them, for example whether a fruit is edible, the sand on the beach comfortable to sit on, or a garment pleasant to wear. That is in everyday judgments we call various types of materials as being more or less soft as covered by our different softness dimensions. Yet other researchers appear to promote the idea of different softness dimensions: e.g., Di Luca (2014) defined haptic softness generally, as the subjective impression of compressibility and deformability characteristics of things and materials, meaning that softness can be interpreted as the perception of a material's response to change through physical interaction. All our softness dimensions would fall under this definition. Previous works by other groups have extended the notion of softness to different dimensions by promoting percepts of firmness, viscosity or surface softness (Giordano & Avanzini in (Di Luca, 2014); Caldiran et al., 2019; Klatzky, 2019; Jones, 2019; Dovencioglu et al., 2021). This research together with our results provide strong evidence in support of the notion that perceived softness has multiple dimensions.

2.5. Conclusions

Results show that participants actively and finely adapt their EPs to combinations of task and material and support the idea of multiple softness dimensions. These findings might be of interest to several applied fields, including robotics, where an understanding of the haptic perceptual space of material qualities could help to optimize the grasping and exploration abilities of autonomous agents (Hoelscher et al., 2015) or to develop more faithful prosthetics (Zhao et al., 2006).

3. Materials in action: The look and feel of soft

A similar version of this manuscript has been posted to bioarXiv and is currently under revision: Cavdan, M., Drewing, K., & Doerschner K. (under revision). Materials in action: The look and feel of soft. Journal of Vision.

The softness of objects can be perceived through several senses. For instance, to judge the softness of our cat's fur, we do not only look at it, we also run our fingers in idiosyncratic ways through its coat. Recently, we have shown that haptically perceived softness covaries with the compliance, viscosity, granularity, and furriness of materials (Dovencioglu et al.,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 visual-static condition participants were presented with close-up photographs of the same materials, and in the visual-dynamic 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 between the three experimental conditions. With a few exceptions, this correspondence tended to be strongest between haptic and visual-dynamic conditions. These results are discussed with respect to information potentially available through the senses, or through prior experience, when judging the softness of materials.

3.1. 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 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 et al., 2016; Sahli et al., 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 in idiosyncratic ways 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 et al., 2019; Dovencioglu et al., 2020), - but also indirectly, by looking at it (Bergmann-Tiest & Kappers, 2007; Giesel & Zaidi 2013; Schmidt et al., 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 attentions in haptics community for quite a while (Lederman, 1974; Srinivasan et al., 1990; Srinivasan & LaMotte, 1995; for a review see: Bergman-Tiest, 2010) – increasingly so in the past few years (Cellini et al. 2013; Drewing et al. 2018; Vardar et al. 2019; Mezger & Drewing, 2019; Cavdan et al., 2019; Dovencioglu et al., 2020; Cavdan et al., 2020; see Okamoto et al., 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 warmness (cold/warm), hardness (hard/soft), micro and macro roughness, and friction (moistness/dryness, 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 (Alley et al., 2020; Schmidt et al., 2017). Especially, when we watch objects move and materials deform, impressions of material qualities can be perceived quite vividly (van Assen et al. 2019; Schmid & Doerschner, 2018; Alley et al., 2020; Schmidt et al., 2017; Bi & Xiao, 2016; Doerschner et al., 2011; Mao et al. 2019; Marlow & Anderson, 2016; Yilmaz & Doerschner, 2014; Sakano & Ando, 2010).

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 (Dovencioglu et al., 2020) 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 et al., 2018; Cavdan et al., 2019; Zoeller & Drewing, 2020; Cavdan et al., 2020). We know that observers can estimate the weight of lifted objects by just observing the lifting motion (Bingham, 1987; Hamilton et al., 2004; Hamilton et al., 2005; Auvray et al., 2011; Maguinness et al., 2013), and more recent work has shown that humans can distinguish compliance by observing someone else's finger motions (Cellini et al. 2013; Drewing & Kruse, 2014). Similarly, there has been evidence that visually observing exploratory hand motions of others can yield impressions of material qualities (Yokosaka et al., 2018; Wijntjes et al., 2019).

Do these sources of information, i.e., images, motion/deformations of the material, watching hand movements and haptic exploration[1], 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. While cue combination studies might provide some important insights into how information is integrated (Lederman et al., 1986; Lacey & Sathian, 2014; Cellini et al., 2013; Adams et al., 2016; Paulun et al., 2019; Wolfe, 1898; Ellis & Lederman, 1999), it is also of interest to understand how much the perception of a material quality from one source of information corresponds to the

[1] Also, auditory cues play a role in material perception, however these are not the focus of this investigation (Klatzky et al., 2000; Fujisaki et al., 2014; Fujisaki et al., 2015).

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 et al. (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 et al. (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 & Drewing 2011; Cellini et al. 2013; Di Luca, 2014; Punpongsanon et al., 2015; Kitada et al, 2019; Zoeller et al., 2019) is in fact a multidimensional construct, that consists of several qualities such as surface softness, granularity, and viscosity (Cavdan et al., 2019; Cavdan et al., 2020; Dovencioglu et al., 2020). 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; Cavdan et al., 2020; Dovencioglu et al., 2020). 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 condition). We compare results of the visual experiment to data from a corresponding haptic study by our group (Cavdan, Doerschner, & Drewing, 2019). 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, since ratings in the former are based on the same type of indirect information (i.e., visual; Paulun et al., 2017; van Assen et al., 2018; Wijntjes et al., 2020). Given previous results by (Wijntjes et al., 2020), 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.

3.2. General Methods

3.2.1. 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 (Dovencioglu et al., 2020; Cavdan et al., 2019). 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 condition, and still photographs of images of the materials in the static 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 (see Cavdan et al., 2019 for more details), which we refer to as haptic condition in the remainder of this paper.

3.2.2. Participants

Ninety students participated in the experiments: static visual condition: 20 females, 10 males; mean age 23.4 y., range: 20-31y; dynamic visual condition: 21 females; age range: 20-33; mean age:25.1; haptic condition: 21 females, 9 males; mean age: 23.6 years; range: 18-38 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 (2013).

3.2.3. Stimuli

Materials items were the same as in our previous haptic study (Cavdan et al., 2019), and included those that had resulted in extreme positive or negative values on four softness-related (Deformability, Fluidity, Hairiness, 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 3.1, and Dovencioglu et al., 2020, Cavdan et al., 2019).

Still images. To generate still photographs of all 19 materials we placed individual materials on a green cloth (Figure 3.1). Where possible we added traces of a manual manipulation (e.g., playdough with indentation of fingers, sand with some run-through marks) in order to increase the available shape cues to the respective material properties. Photographs were taken close-up a using a Sony Digital 4K Video Camera Recorder which took 60-bit images at a spatial resolution of 3840 × 2160 pixels (white balance disabled), and with materials illuminated by two 1320 lumen light bulbs placed left and right to the material. The white balance was turned off. This setup yielded a quite natural look, minimizing any harsh shadows. Postprocessing of images centering of the material and cropping to a size of 2049 x 1464 pixels (The Gimp development team, 2019).

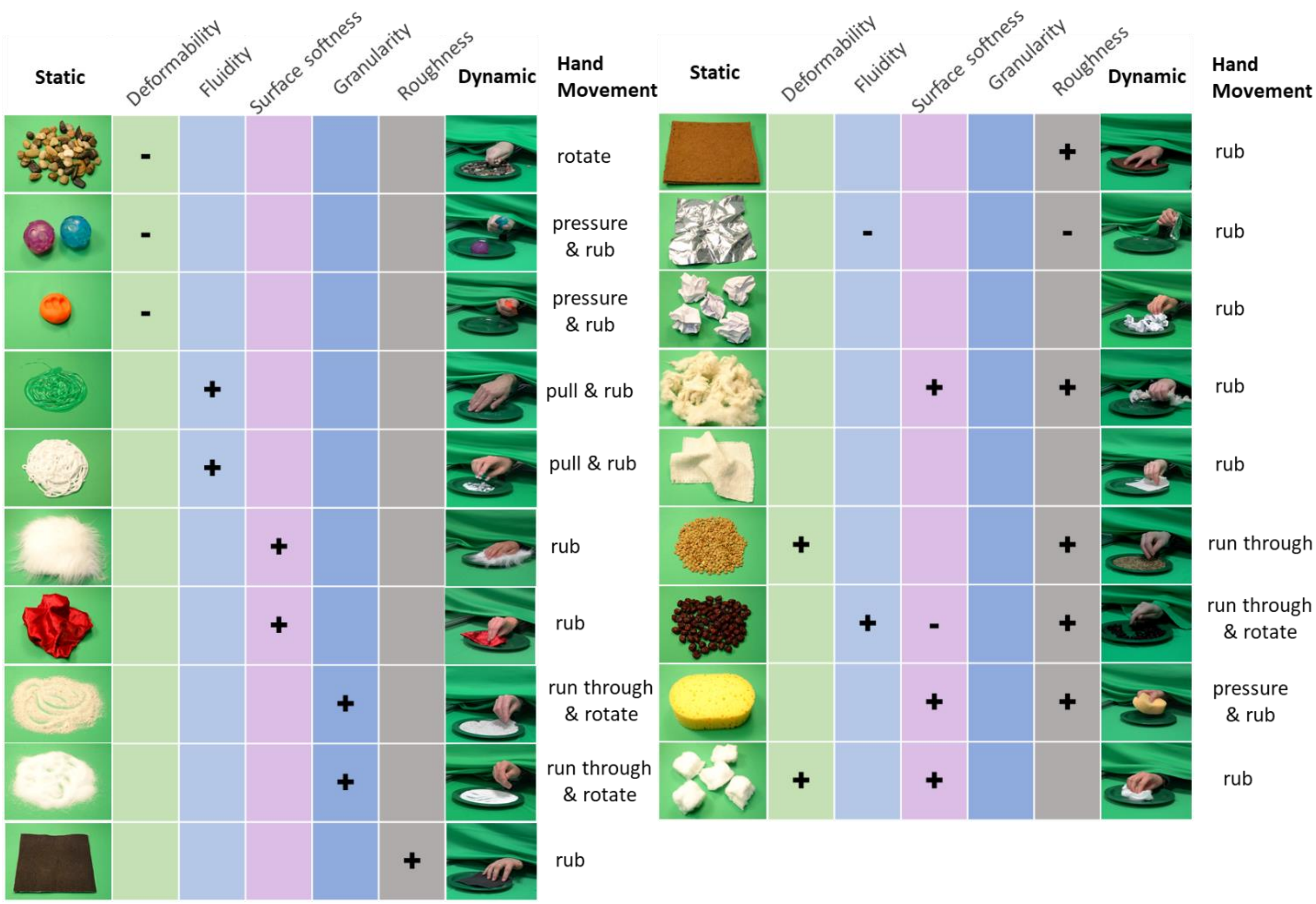

Figure 3.1. Images used as static stimuli (column 1), associated dimensions of the materials (negative loadings (-), positive loadings (+)), associated hand movements from Cavdan et al. 2019 (column 7), and example frames from dynamic stimuli (column 8). The names of the materials

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.

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

First, we determined the either one or two most frequently used, typical exploratory hand movements per material using the taxonomy of by Cavdan et al. (2019, 2020). 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., 2019, page 2). Definitions of all exploratory hand movements can be found in Supplementary Methods 1. Most frequently associated hand movements for each material can be found in Figure 3.1, 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 x 1080 pixels. This resulted in 3 matched sets of 19 clips each (one clip per material). Figure 2.1, column7 shows sample snapshots from the movies used in the dynamic condition.

Adjectives. Stimuli were rated on the same 15 sensory adjectives that we used in the previous haptic experiment (Cavdan et al., 2019). These adjectives had been selected based on their association (positive or negative) with the above-described softness dimensions or the control dimension (Dovencioglu et al., 2020). These were *soft, elastic, hard, inflexible, moist, wobbly, sticky, sandy, powdery, granular, velvety, fluffy, hairy, rough* and *smooth* (see Cavdan et al., 2019 for more details of the selection criteria for adjectives).

3.2.4. Apparatus

In the static condition, stimuli were displayed on a Samsung UHD (U32D970Q) 32” Professional LED monitor (resolution: 3840 x 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° in width and about 20° in height.

In the dynamic information condition, stimuli were presented on a DELL UltraSharp monitor (resolution: 2560 x 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° in width and about 15° in height. Videos were played at a rate of 30 frames per second.

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

In the previous haptic experiment (Cavdan et al., 2019), we used a curtain to hide the materials from the participant’s view and active noise cancelling headphones so 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., 2019).

3.2.5. 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 x 15 adjectives) in about one hour. The order of material-adjective pairs was randomized, every participant saw every material-adjective pair only once (Figure 3.2).

Dynamic condition. The procedure in the dynamic condition was similar to the static condition except that, instead of a static image, observers now saw a 6 second movie clip showing the exploration of a material (see Figure 3.2). Observers had to rate all three sets of dynamic stimuli, each set on a separate day. Each session (19 movie clips x 15 adjectives) took about 1 hour.

Haptic condition. A typical trial in the haptic condition is shown in Figure 3.2. 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.

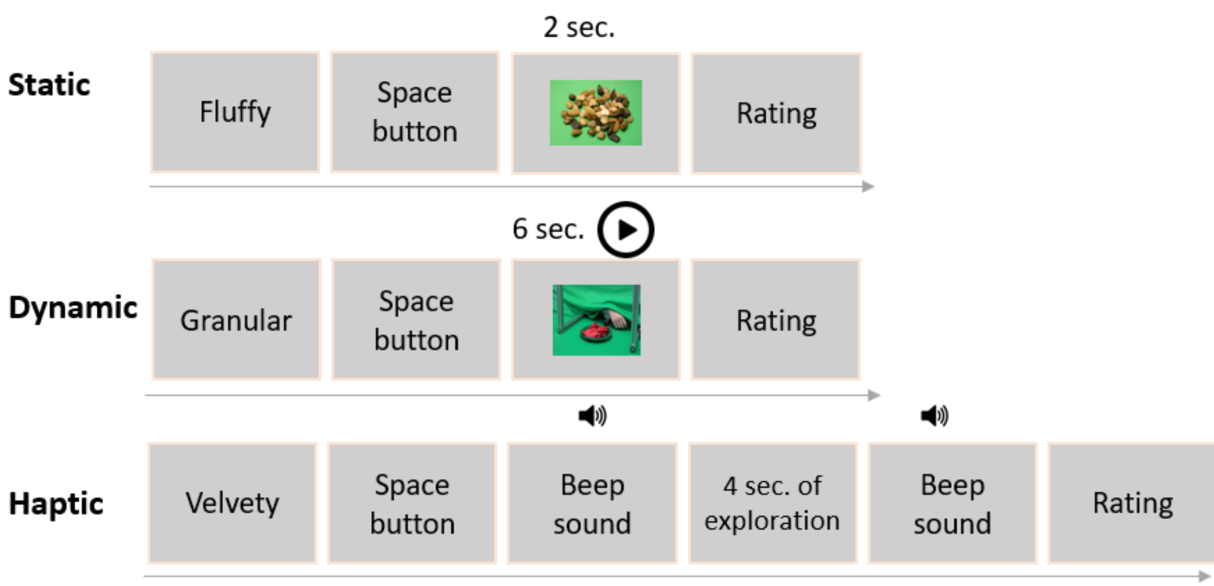

Figure 3.2. Time course of a trial across conditions in the experiment. First, in all conditions, the adjective to be rated appeared on the screen. After pressing the space button an image was presented on the screen for 2 seconds in static and a video presented on the screen for 6 seconds

in the dynamic 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.

3.2.6. 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. Since we acquired 3 data points for each material-adjective combination in the dynamic condition (i.e., three videos for each material-exploration stimulus) we used the average of these 3 scores in the consistency- and all subsequent analyses. Next, we performed separate PCAs for static and dynamic conditions based on average observer data from material-adjective pairs (19 materials x 15 adjectives = 285 data points). 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 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 up 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, dynamic, 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 dimension 1 vs haptic dimension 1: static dimension 1 vs haptic dimension 2 etc.).

Lastly, we directly investigated whether there were significant 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. Finally, we determined the 95% percentile of this distribution, and report the conditions in which rating difference exceeded this cut-off value.

3.3. Results

3.3.1. Interobserver consistency

Overall, all interindividual correlations between participants' ratings in static and dynamic conditions where significant ($p < .01$), and ranged between .41 - .81 and .41-.95, respectively (also see Supplementary Figure 1 & 2). These values were comparable to previously reported results in the haptic condition (.45 - .86) and suggest that participants interpretation of the perceptual meaning of adjectives tended to agree. All subsequent analyses were done on ratings that were averaged across participants.

3.3.2. PCA for static and dynamic rating data

Since participants showed high consistency in their rating data, we performed next covariance PCAs for static and dynamic conditions. The Keyser-Meyer-Olkin (KMO) criterion was .4, and .5 for the static and dynamic conditions, respectively, which are borderline values. However, Bartlett's test of sphericity was significant for both conditions ($p<.01$): χ^2 (105) = 370.32, χ^2 (105) = 360.03, suggesting that the observed correlations between adjectives were meaningful. Components were extracted according to the Kaiser-criterion and rotated using the varimax method.

In the static condition we extracted three components explaining 83.9% of the total variance (see Table 3.1.). 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, moist.*

In the dynamic condition we extracted four components explaining 89.2%. While three of the components were rather similar in their structure to the static condition *(surface softness* (25.2%, *soft, velvety, hairy,* and *fluffy*), granularity (23.7%, *granular, sandy, powdery, smooth*), viscosity (21.8%, *wobbly, sticky, moist, 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, moist*), *granularity* (20.6%, *granular, sandy, powdery*), *deformability* (17.8%, *elastic, hard, inflexible*)) as well as one component related to the roughness of the material (*roughnes*s, 9.5%, *rough, smooth*).

While 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, which 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, viscosity) between static, dynamic and haptic conditions. This analysis aims to map two multi-dimensional 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 between the three conditions we obtained values of .19 (static vs dynamic), .20 (static vs haptic), and .25 (dynamic vs haptic).

These values were all comparably low (also see Supplementary Figure 4), indicating a rather high similarity between the three perceptual spaces, spanned by the dimensions of surface softness, granularity, viscosity (also see Supplementary Figure 3). Thus, we determined that structural similarity was sufficient to proceed with a combined PCA for static, dynamic and haptic rating data, which would allow us to make more fine-grained comparisons between the static, dynamic and haptic spaces of perceived softness.

3.3.3. Combined PCA for static, dynamic, and haptic rating data

A Keyser-Meyer-Olkin (KMO) value of .68 and a statistically significant Bartlett's test of sphericity ($\chi 2(105) = 1225.62$, $p < .01$) suggest that a PCA was indeed appropriate for the combined dataset (Francis & Field, 2011). The combined PCA yielded three components explaining 82.16 % of the total variance. The adjectives *soft*, *fluffy, hard, velvety*, *hairy*, *inflexible* and *elastic* loaded high on the first component, which explained 34.5 % of the total variance, and given its loading patterns we named it *surface softness/deformability*. The adjectives *sandy*, *granular, powdery*, and *rough* loaded high on the second component, which explained 25.5 % 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 22.16% of the variance. Table 3.2. shows the adjective loadings for each of the three components in this combined PCA analysis and Figure 3.3 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.

Table 3.1. Adjective loadings after rotation for static and dynamic 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: .68 static, .62 dynamic, and .74 for haptic sequentially) and load higher on 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.

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	.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 3.2. Rotated Adjective loadings obtained from the combined PCA analysis (static, dynamic and haptic conditions). Color-codes, font styles, and criterion for significance (>40% of mean variance= .67) are as in Table 3.1.

Adjective (English /German)	I. Surface softness/Deformability	II. Granularity	III. Viscosity
Explained variance	34.54%	25.46%	22.16%
Soft / weich	**1.06**	-0.20	0.37
Fluffy / flauschig	**1.19**	-0.16	-0.43
Hairy / haarig	**0.86**	-0.12	-0.43
Velvety / samtig	**0.73**	-0.06	-0.16
Hard / hart	**-0.85**	0.22	-0.48
Inflexible / unbiegsam	***-0.64***	0.43	-0.15
Elastic / elastisch	*0.52*	-0.34	0.39
Sandy / sandig	-0.23	**1.08**	-0.12
Powdery / pulverig	-0.14	**0.94**	-0.03
Granular / körnig	-0.53	**1.06**	-0.16
Rough / rau	-0.29	***0.63***	-0.40
Smooth / glatt	-0.37	*-0.50*	0.17
Sticky / klebrig	-0.13	-0.07	**0.98**
Moist / feucht	-0.15	-0.14	**0.96**
Wobbly / wabbelig	0.14	-0.25	**0.85**

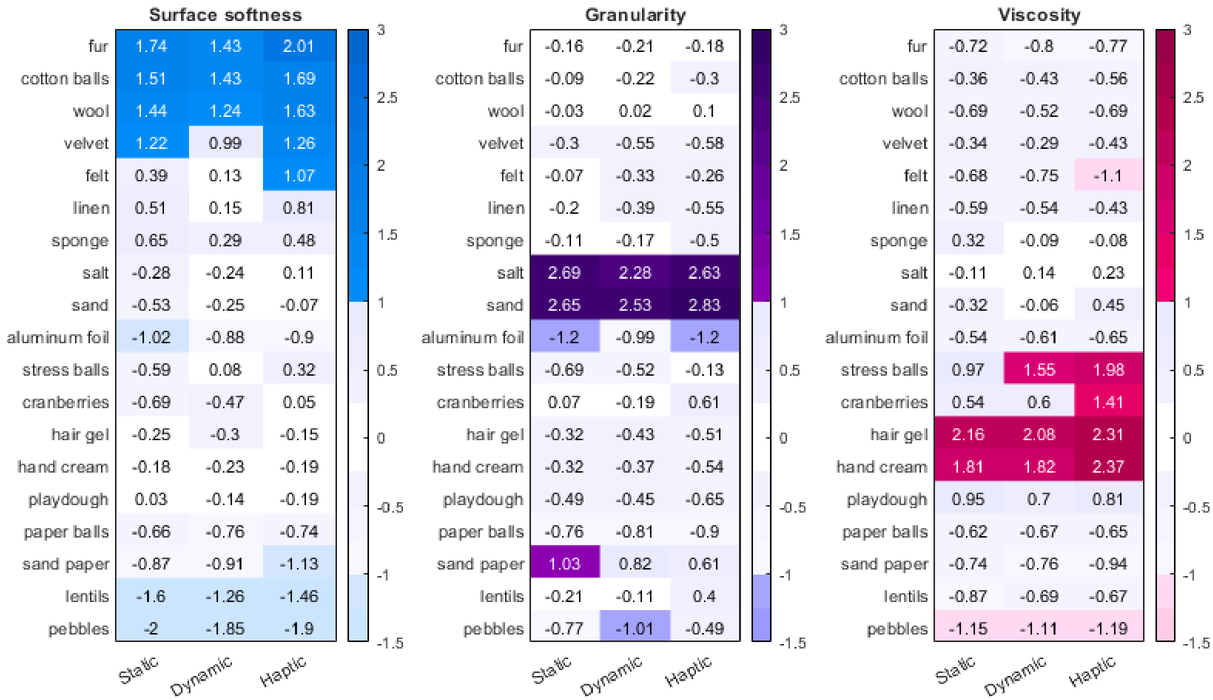

Figure 3.3. Rotated component scores (Bartlett scores) of materials - in each perceptual softness dimension: surface softness, granularity, and viscosity dimensions - for haptic, dynamic, and static conditions, respectively. Darker, saturated colors indicate positive loadings and desaturated, lighter colors represent negative loadings. Light violet and white areas indicate that loadings were larger than –1 standard deviation, or smaller than 1 standard deviation.

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

In order to determine the similarities between the static, dynamic, and haptic perceptual spaces of perceived softness, we compared the correlation scores of the Bartlett scores of the three softness dimensions (*surface softness, granularity*, *viscosity*) across all materials (Figure 3.3). Figure 3.4 shows that overall, these correlations were high between the three perceptual spaces, with the highest correlation between the two visual spaces (static & dynamic, (r^2=.95 p <.01), followed by the correlation between dynamic and haptic (r^2=.94, p <.01), and between static and haptic spaces (r^2=.89, p <.01).

We next tested our two 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. The correlation between dynamic and static spaces was indeed significantly larger than that between static and haptic spaces ($p < .01$, one-tailed), however it was not significantly larger than the dynamic-haptic correlation. Pertaining to our second hypothesis we found indeed that the correlation between the dynamic-haptic spaces was larger than that between static and haptic spaces ($p = 0.03$, one-tailed).

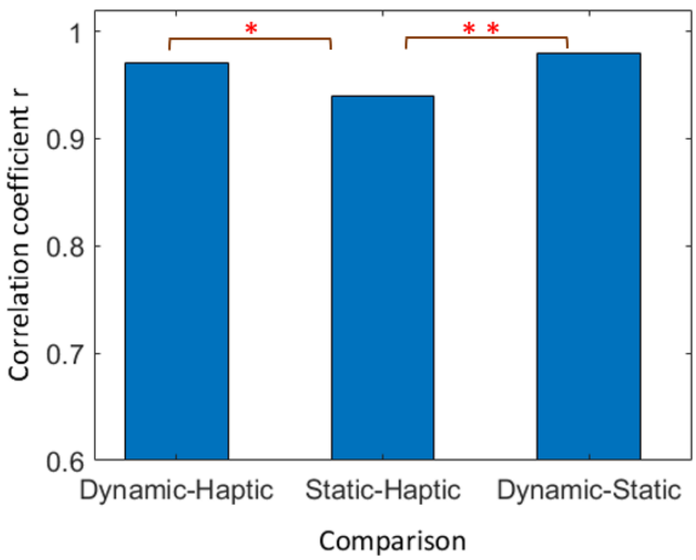

Figure 3.4. Comparisons of correlation coefficient *r* across dynamic visual information-haptic, static visual information- haptic, and dynamic visual information-static visual information conditions. Asterisks represent significance levels (*: $p < 0.05$, **: $p < .01$).

It is further possible that the strength of the correspondence might vary between the respective softness dimensions, i.e., for *surface softness, granularity or viscosity*. To investigate this possibility, we computed the correlations of Bartlett scores also at the dimensional level. As expected, the correlations across conditions (static, dynamic, haptic) *within* the respective dimensions were very high and statistically significant (Figure 5, dark blue colors, all $p < .01$), and correlations across the respective dimensions were low and not significantly different from 0 (light blue colors).

We next put our two hypotheses to test. Regarding our first hypothesis, which states that the correlation between the two visual conditions should be strongest, we find that even though the correlation within *surface softness* between static-dynamic spaces was higher (.974) than that between static-haptic spaces (.956), this difference was not statistically significant. Within *granularity, however* the correlation between static-dynamic spaces (.989) was significantly higher (p =.01, one-tailed) than the correlation between static-haptic spaces (.954; p = .01, one-tailed), indicating a high correspondence between the two visual conditions for this dimension.Within the *viscosity* dimension the correlations between static-dynamic spaces (.975) was higher than the correlation between the static-haptic spaces (.946), however, this difference did not yield statistical significance.

As a reminder, our second hypothesis was that the correlation between the dynamic visual condition and the haptic experiment should be stronger than the correlation between static visual condition and haptic condition. While numerically this trend was true for all dimensions, only for *viscosity* the correlation between dynamic and haptic spaces (.982) was significantly higher than that between static and haptic spaces (.946, p = .03, one-tailed).

These analyses suggest that despite an overall good agreement between static, dynamic and haptic perceptual softness spaces, there are also some interesting differences as to how the softness of materials is represented in each of these spaces. In the next analysis we will analyze the rating differences of observers in the three conditions in order to understand for what material-adjective pairs the ratings of participants differ most.

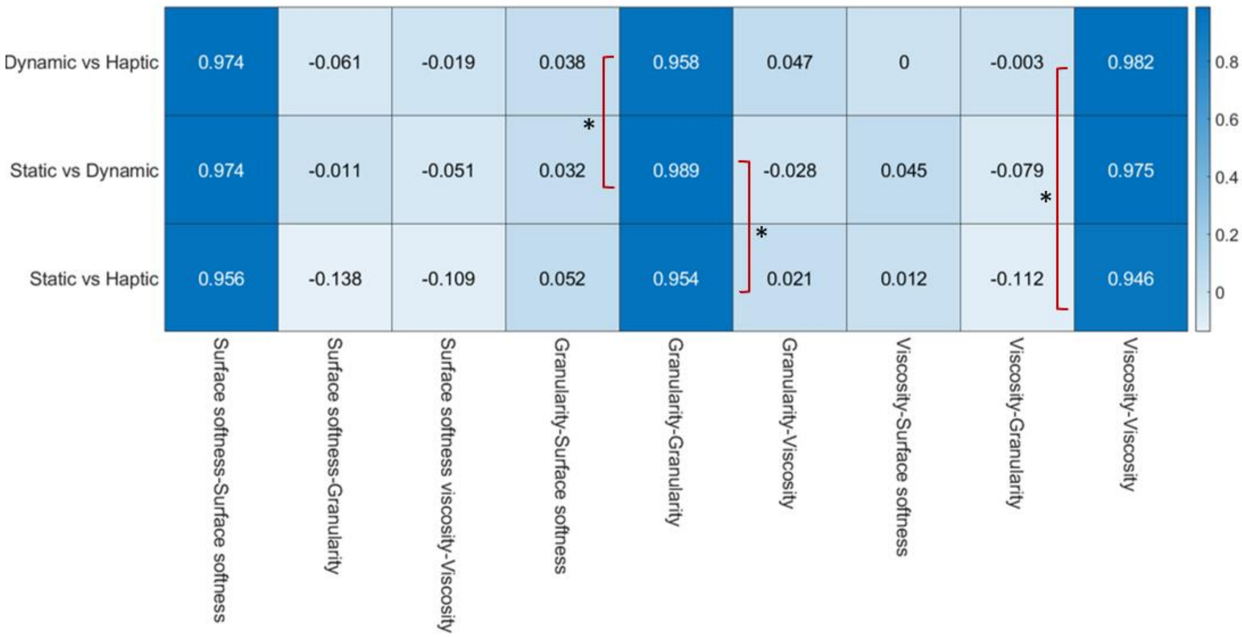

Figure 3.5. Correlations between Bartlett scores across materials for either pair of component scores from the haptic, the dynamic, and the static visual cue conditions. Darker colors (blue) show higher while lighter colors (white) show lower correlations.

Rating differences between static, dynamic and haptic conditions.

Overall, only 35 out of the 855 (285 x 3) rating differences exceeded the determined cut-off value. From these, three groups of difference patterns emerged: In one group there were *always* significant differences between haptic and the two respective visual conditions, but *never* between the two 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 or static conditions, that linen felt softer than it looked, or that fur feels 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, or conversely, the two visual conditions conveyed similar information (consistent with our 1st hypothesis above).

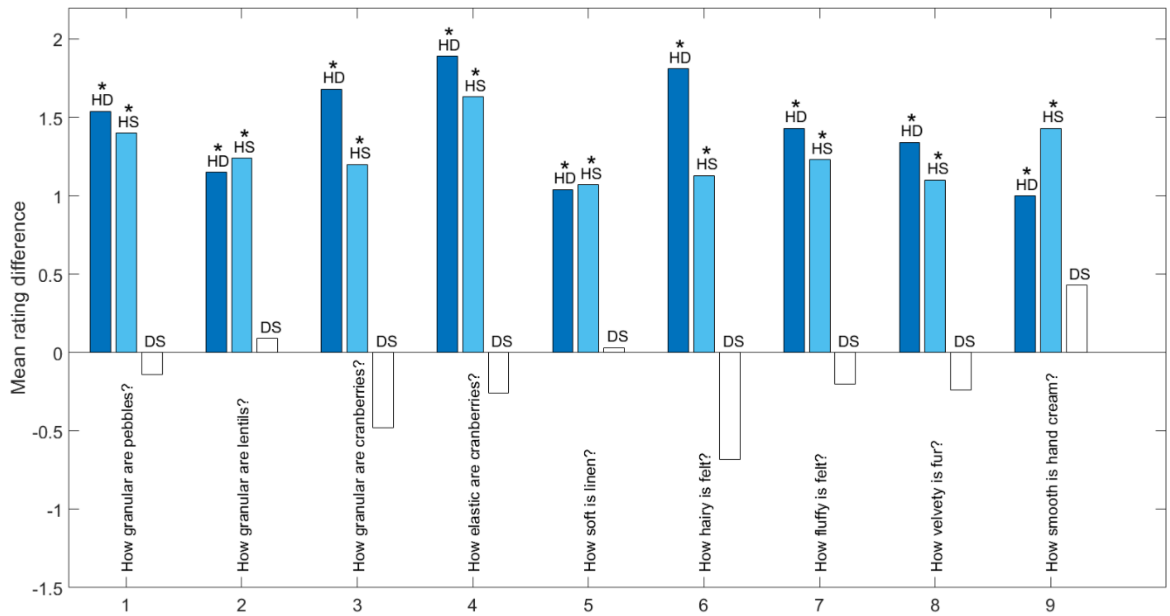

Figure 3.6. Haptic and visual information each convey different material qualities. Mean rating differences between static dynamic and visual conditions for specific material-adjective pairs. HD refers to the differences in rating between haptic and dynamic conditions (dark blue), HS to the differences in rating between haptic and static conditions (light blue), and DS to the differences in rating between dynamic and static conditions (white). * show the mean differences larger than 95% percentile cut off value (see Methods).

In a second group there was *never* a significant difference between haptic and dynamic conditions, but there was for other comparisons (e.g., for haptic-static, or for dynamic-static, Figure 3.7). For example, the softness of sand, salt and cranberries was judged equally in haptic and dynamic conditions, as was the hardness of stress balls. Here, it appears, that dynamic visual condition conveyed similar information as the haptic condition (as we also expected in our 2nd hypothesis above). Additionally, the differences between the two visual conditions tended to be larger than in group one (Figure 3.6), even reaching significance in some cases.

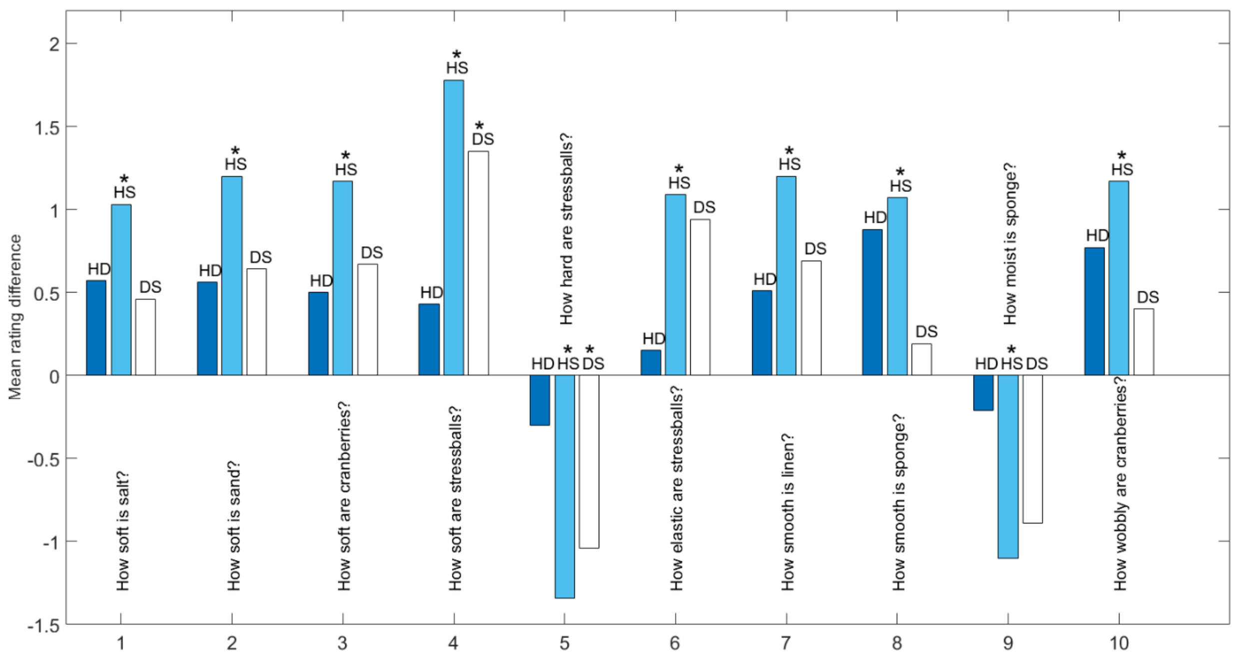

Figure 3.7. Dynamic visual and haptic information convey similar material properties. Mean rating differences between static dynamic and visual conditions for specific material-adjective pairs. Symbols and colors as in Figure 3.6.

Lastly, the third group of differences was the most surprising, containing cases with significant differences between haptic and dynamic conditions *only* (Figure 3.8). This goes directly against our 2nd hypothesis, which proposed that dynamic and haptic conditions should yield 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.

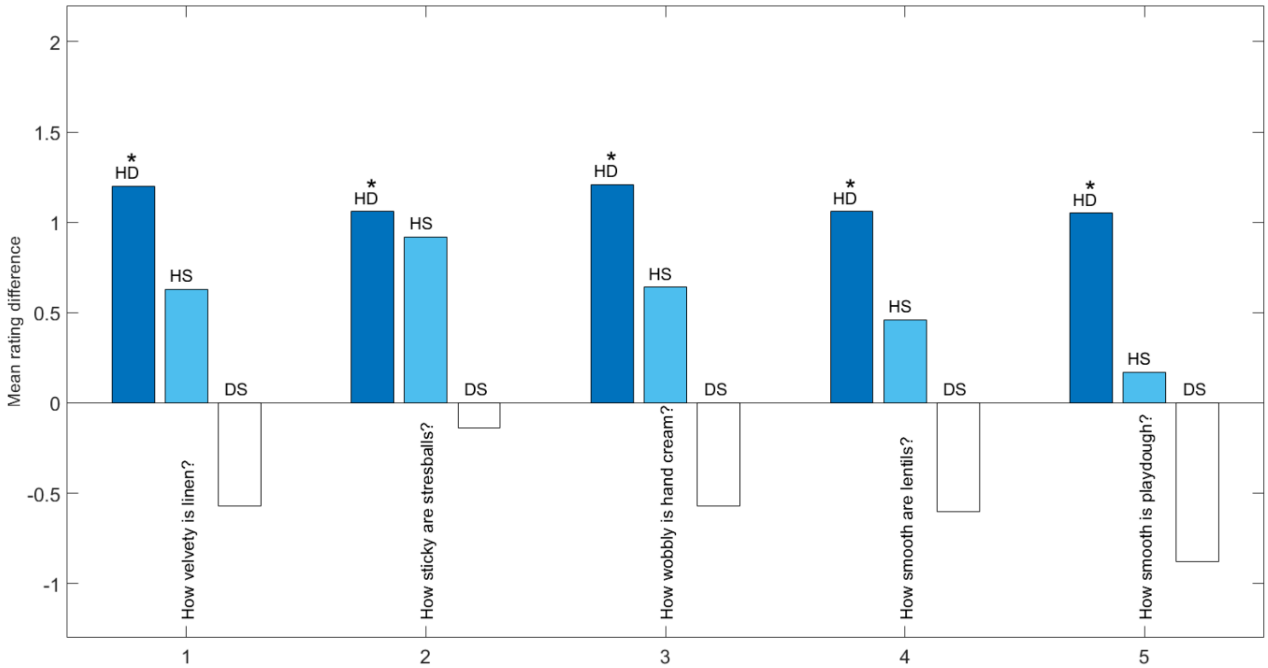

Figure 3.8. Static visual and haptic information convey similar material properties. Mean rating differences between static dynamic and visual conditions for specific material-adjective pairs. Symbols and colors as in Figure 3.6. and 3.7.

3.4. 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. While we think of softness as primarily a mechanical property that can be perceived through touch (Klatzky & Lederman, 1987; Cellini et al., 2013; Okamoto et al., 2013; Di Luca, 2014; Higashi et al., 2019; Kitada et al., 2019; Cavdan et al., 2019; Dovencioglu et al., 2020; Xu et al., 2020) softness can also be judged visually (Drewing et al., 2009; Giesel & Zaidi, 2013; Baumgartner et al., 2013; Bouman et al., 2013; Bi & Xiao, 2016; Bi et al., 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 et al., 2010; Yildirim & Jacobs, 2013; Desmarais et al., 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 whose optical and shape properties strongly resemble the originally experienced fabric, it can elicit the same 'sensation' of soft (also see Schmidt et al. 2017; Anderson, 2011 or Schmid & Doerschner 2019, 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., 2019). *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 (five dimensions) than the visual ones, with the dynamic visual space (four 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, 1936; Lederman & Abbott, 1981; Bergmann-Tiest & Kappers, 2007; Stilla & Sathian, 2008; Baumgartner et al., 2013; Vardar et al., 2019; Xiao et al., 2016).

In particular, we found three softness dimensions: *surface softness, granularity* and *viscosity* that were common to all conditions. While the amount of agreement between visual and haptic experiments is substantial for the softness dimensions of *surface softness, granularity* and *viscosity*, Table 3.1. also shows several interesting differences between these conditions, which we will review next.

3.4.1. Differences in dimensionality

The individual principal component analyses revealed three softness dimensions: *surface softness, granularity* and *viscosity* in all three conditions (static, dynamic and haptic). However, in dynamic 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 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; van Assen et al., 2018; Schmid & Doerschner 2017) 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; Schmid & Doerschner, 2018, Schmidt et al., 2017, van Assen et al., 2018, Bi et al., 2018; Alley et al., 2020), in particular if also manual interactions with the material are shown (Cellini et al., 2013; Drewing & 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., Okamato 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 et al., 2008; Eck et al., 2013), or while matching abrasive papers (Lederman & Abbott, 1981). Guest & 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).

3.4.2. Differences in the perceptual softness space structure

With a combined PCA we were able to zoom in on differences between static, dynamic, and haptic spaces for the softness dimensions common to all three: *surface softness, granularity and viscosity*. As can be seen in Figure 3.4, the overall pattern that emerged when correlating the Bartlett scores between the three spaces (across all 3 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, while *surface softness* was numerically consistent with this general trend (Figure 3.5), there was no significant difference in the correspondence between spaces. For *viscosity*, on the other hand, the correlation between dynamic and haptic spaces was significantly stronger than that between dynamic and static spaces. What might be the reason for this? Inspecting, Figure 3.3, might provide a hint: the Bartlett scores of the material *stress balls* show high values in *viscosity* of haptic and dynamic spaces but not in the static space. *Stress balls,* although being quite squishy and sticky to the touch, do in their 'resting' shape 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 high relevance of dynamic visual information in transporting viscosity. While 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 will not be able 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 significantly higher than between dynamic 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. 2. These visually estimated properties differ from those estimated by touch. This might be because vision strongly relies 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).

3.4.3. Differences in ratings

Our interpretations above suggest that the differences that we find between the perceptual softness spaces of static, dynamic 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. Only 35 rating differences survived this procedure, again supporting the idea that perceived softness appears to be similar between visual and haptic spaces. Those material-adjective combinations that yielded significant rating differences between conditions fell into three categories: 1) haptic and visual information each convey different material qualities 2) dynamic visual and haptic information convey similar material properties, 3) static visual and haptic information convey similar material properties. We will discuss each one of these next.

Haptic and visual information each convey different material qualities. For the material adjective combinations in this group, it appears that haptic information conveys information about material properties that is distinct from that conveyed by visual information, or conversely, the two visual conditions conveyed similar information. Looking at the specific cases for which this occurs we see that this pattern emerged primarily for judgments related to the granularity (how granular and surface softness (how hairy, velvety, hairy). We already offered an explanation about the differences between visual and haptic perception of granularity above (vision relies on particle size when touch might rely on interaction characteristics of the particles, see section 'differences in the perceptual softness space structure'). Why do we, however, not see such differences for granularity judgments of sand. It is possible sand or salt are materials that most observers are very familiar with, and when identifying the materials, memories of interacting with the material might become activated enabling participants to make these judgments. For example, found that perceived softness in haptic experiments is influenced by memory (Metzger & Drewing, 2019), and haptic experiences (Kangur et al., 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 be made for judgments of *surface softness*. Figure 3.6 shows that the differences between visual and haptic conditions are generally positive suggesting that felt fur and linen were judged *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.

Dynamic visual and haptic information convey similar material properties. In contrast to the first group, adjective-material pairs in this group elicited similar judgments in dynamic and haptic experiments, whereas the difference to ratings in the static condition increased (height of white bars in Figure 3.7). Why did static visual information yield different ratings than haptic or dynamic conditions? Figure 3.7 illustrates that this kind of pattern emerged primarily for judgments of *surface softness* (how soft), but also for judgments of *deformability* (how elastic, how hard), or *viscosity* (how moist, 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. How can we reconcile the data from Figures 3.6 and 3.7? Let's consider the stimuli in the dynamic condition: the movies contained three sets of cues to material properties 1) pictorial cues, 2) deformation cues and 3) interaction cues. While 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 and haptic ratings. We gave already a concrete example along this line with the 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 were not effective for the first group of material-adjective pairs, would be an interesting question to pursue in future research.

Static visual and haptic information convey similar material properties. Although this occurred just for 5 material-adjective pairs, this was the most interesting pattern, as it was in contradiction to our hypothesis, that dynamic and haptic conditions should yield more similar outcomes (i.e. the pattern observed in group 2). Why might haptic and static 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 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, 2020) 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 condition we focused on the most frequent hand movement for a material type, neglecting the effect of task (since 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 condition. This possibility could be explored in future work.

3.5. Conclusion

Softness is a prominent property that renders an object useful or useless, appealing, or repulsive to us. This study shows that perceived softness is a multidimensional construct, and 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, we also found some noteworthy differences. We argue that these differences appear primarily to 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.

4. Constraining haptic exploration with sensors and gloves hardly changes the multidimensional structure of softness perception

A similar version of this manuscript is currently under revision: Cavdan, M., Ennis, R, Drewing, K., & Doerschner K. (accepted for publication). Constraining haptic exploration with sensors and gloves hardly changes the multidimensional structure of softness perception. IEEE Proceedings.

Humans typically interact with the environment using bare hands. However, sometimes this is not possible or not preferred, e.g., when wearing protective gloves for work or sensor gloves in mixed/augmented reality (AR). Also, studying softness is highly important since it makes use of tactile and proprioceptive cues and it might be highly sensitive to restrictions. Here we tested how corresponding haptic constraints affect perceived softness. Participants manually explored and rated 10 materials on 15 sensory adjectives under four constraint conditions: bare hand, open-fingered glove, open-fingered glove with rigid sensors, and full glove. The materials represented extreme values on different softness dimensions; the adjectives were chosen to assess these dimensions. Principal Component Analysis (PCA), Procrustes distances, and correlation analyses showed that across constraint conditions, softness perception is overall highly similar. However, when we inspected responses on a more detailed level, per material-adjective combination, we observed that the glove condition differed from the others especially for judgments on surface softness. Overall, the results suggest that sensor gloves hardly change the perception of different dimensions of softness if fingertips are left bare.

4.1. Introduction

The hand is one of the most important and vital tools for people to efficiently and intuitively interact with the environment. For instance, we automatically take a fruit or vegetable in our hands and apply various pressure levels to see whether it is edible. We usually perform these kinds of everyday tasks with bare hands, which is most efficient [Klatzky et al., 1985; Klatzky et al., 1993; Lederman & Klatzky, 2004). However, we also encounter various constraints on exploration during our activities, when bare-hand exploration is not possible or not preferred. For example, we use warm gloves in winter, protective gloves (sometimes quite stiff ones) for work or combine augmented reality setups with different kinds of sensor gloves.

Previous research addressed the effect of free exploration restriction on object identification using glove and open-fingered glove (Klatzky et al., 1993; Lederman & Klatzky, 2004). However, none of these studies investigated the effect of restrictions on softness perception. It is important to study since it makes use of tactile and proprioceptive cues and it thus might be highly sensitive to restrictions. For example, suppose we are wearing gloves and walking home on a cold winter day and suddenly would have to clean our nose. With gloves on, it will be more difficult to accurately find a soft, foldable handkerchief in our pockets and we will need to remove the glove in a moment of exasperation. The handkerchief is perhaps an extreme example of soft objects, but the example highlights that a glove can reduce our tactile perception, since it is a barrier between the sensors in our skin and the rest of the world, and certain kinds of gloves could reduce or alter our proprioceptive perception, since if a glove is soft and thick or stiff and rigid, then its material acts as a filter for the forces that normally provide feedback to our joints about how bendable, flexible, or malleable an object is. Thus, it is reasonable to expect that gloves could have a significant effect on haptic softness perception in particular.

In the context of grip dynamics or AR research, understanding the effect of gloves is important because the hand-tracking sensors that are necessary for such work are often attached to gloves. If haptic perception is altered due to gloves, then this could lead to unexpected or unwanted changes in grip dynamics. Taken together, assessing the overall effect of gloves in the context of softness perception provides a good foundation for understanding the effects of sensory and proprioceptive restriction on haptic perception in general.

Recently, we have shown that perceived softness is a multidimensional construct which consists of furriness, viscosity, granularity, and deformability (Cavdan et al., 2019; Cavdan et al., 2021). Here, we use this fine-grained differentiation as a tool to measure how gloves influence different aspects of perceived softness. To this end, we had participants perform a semantic differential task (rating how a material applies to an adjective) under four different experimental conditions (i.e., *bare hands*, *full glove*, *open-fingered glove*, and *open-fingered glove with rigid sensors*). The materials represented extreme values on the softness dimensions of deformability, viscosity, granularity, and surface softness; the adjectives were chosen to assess these dimensions. We first performed a Principal Component Analysis (PCA) on the ratings per constraint condition and compared the four perceptual spaces by calculating Procrustes distances. Because all four spaces were similar and Procrustes distances were low, we subsequently performed a combined PCA to make more fine-grained comparisons using correlation analyses. Finally, we investigated the similarities between constrain conditions at the material-adjective level.

4.2. Methods

4.2.1. Participants

23 students (2 males, mean age: 22.5 years; age range:19-29) from Giessen University joined the experiment. They were compensated with either 8 €/hour or course credits for their time. All of the participants were naïve to the purpose of the experiment and spoke German at a native-speaker level. None of the participants reported motor, sensory, or cutaneous impairments.

4.2.2. Setup, materials, and adjectives

Noise cancelling headphones (Sennheiser HD 4.50 BTNC) were used to dispose of sounds that could be caused by the exploration of materials and to give beep sounds which signal start and end of a trial (i.e., exploration period). Using Psychtoolbox routines (Brainard, 1997; Kleiner et al., 2007), the experiment was programmed in MATLAB 2019b (MathWorks Inc., 2007). A monitor was placed to the left side of participants to present the adjectives and a numpad, placed next to it, was used to collect responses.

Participants were seated at a table where the stimuli were presented. We mounted a horizontally rotatable armrest at the table in order to ensure that all participants explored the stimuli from the same distance and to reduce discomfort. A curtain was used to hide the materials from the participants' view. The experimenter sat behind the curtain and placed the plates (diameter 21.5 cm) containing the materials, as needed.

Figure 4.1. Illustrations of *bare hand*, *open-fingered glove*, *glove with rigid sensors* and *full glove* conditions (sequentially) used during the experiment.

We used golf gloves to make sure they fit well to a participant's hand and the size of each glove was chosen depending on the size of the participant's hand (i.e., small, medium, or large). We also used mock sensors instead of real ones, because our aim in this experiment was not to follow the participant's hand movement, but only to investigate the effect of sensors on perception. Therefore, we used less costly plastic sensors. The mock sensors were made of polylactic acid. In total, there were 16 sensors, and the sensors were connected to each other with fibres which was a complete replica of a Synertial Cobra motion capturing glove (Synertial Inc.). The golf gloves were made of a mixture of leather (60%), polyester (31%), polyurethane (5%), and elastodiene (4%). Micro-perforations available on the fingers provided some air circulation. The fingers of the gloves were made of leather. While the gloves were used as they were in the *full glove* condition, for the *open-fingered glove* and *glove with rigid sensors* conditions, the fingers of the gloves were cut at approximately 5 cm length (see Figure 4.1).

Materials and adjectives were selected to be representative for different material dimensions from (Cavdan et al., 2021). We selected materials which in that study had highly loaded on one of the four softness dimensions of deformability, granularity, furriness, viscosity, or on the control dimension (roughness) in a principal component analysis (PCA). The materials and their corresponding categories are as follows: deformability: play dough and sponge; granularity: salt and sand; furriness: cotton balls and fur; viscosity: hand cream and hair gel; roughness: sandpaper and felt.

Also, all of the adjectives used in (Cavdan et al., 2021) were chosen for the current study. Adjectives and the associated dimensions are as follows: furriness (fluffy, hairy, soft, velvety), viscosity (moist, sticky, and wobbly), granularity (sandy, powdery, and granular), deformability (hard, inflexible, and elastic) and roughness (smooth and rough).

Due to Covid-19 regulations, the experiment room was ventilated every 20 minutes during data collection. Also, all of the materials were replaced, and the room was disinfected before each participant. Participants were only allowed to participate if they did not show any symptoms of Covid-19.

4.2.3. Design and procedure

Each participant rated 10 *materials* according to the 15 *adjectives* in each of the four constraint *conditions.* The constraint conditions were *bare hand, full glove, open-fingered glove,* and *open-fingered glove with rigid sensors* (Figure 4.1). In the *bare hand* condition, participants did not wear gloves. In the *full glove* condition, participants wore unmanipulated normal golf gloves (Figure 4.1), while in the *open-fingered gloves* condition, we cut the fingertips of the golf gloves. Finally, for the *open-fingered glove with rigid sensors* condition, we cut the fingertips of the golf gloves and mounted mock sensors to the hand. Sensors were placed on the joints of each finger and one on the pisiform bone. We secured the sensors with double-sided tape. The order of the conditions was counter-balanced across participants.

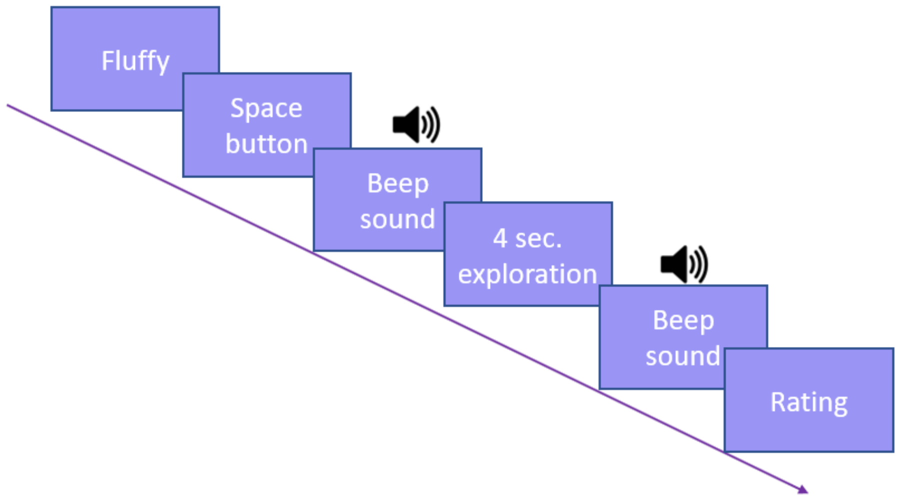

Figure 4.2. Time course of a trial. Each trial started with the presentation of an adjective until the participant pressed the space button. Then a beep sound signalled the start of 4 seconds of exploration time and another beep sound signalled the end of the exploration. Finally, the participant rated the adjective by pushing a button on the numpad.

After some initial instructions participants were equipped with the glove/sensors corresponding to their constraint condition. The experiment started with three practice trials in order to familiarize participants with the setup. The materials and adjectives used for practice were not included in the actual experiment. During each trial in the actual experiment, we presented first an adjective to be judged, until the participant pressed the space button with their left hand. Then a beep sound signaled the start of four seconds of exploration time, during which the participant was free to explore the material. After those four seconds, another beep sound signaled the end of trial. Then, the participant rated how much the adjective applied to the explored material (1 = not at all, 5 = fully applied) by pressing a button on a numpad with their left hand. There were 150 trials in total per condition (15 adjectives, 10 materials) and these trials were divided into 10 blocks. In each block, a randomly selected material was presented, and participants rated all of the adjectives for the given material – the adjectives were also presented randomly. The whole experiment was split over four 50 minutes sessions, which were held on different days. In total, the experiment took about three and a half hours.

4.2.4. Data analysis

First, we analyzed consistency across participants by calculating pair-wise correlations between each participant with the remaining participants (responses across all materials and adjectives), separately for each condition. Second, we performed covariance-based Principal Component Analysis (PCA) separately on ratings for each constraint condition. We checked whether the data was suitable for PCA using Bartlett's test of sphericity and Keyser-Meyer-Olkin (KMO) values.

Using Bartlett's method, we calculated factor scores for each constraint condition. We used these values to calculate Procrustes distances between each perceptual space (i.e., perceptual responses in each constraint condition). If these distances between spaces were low, then we followed up with a combined PCA that allowed us to assess fine-grained similarities or differences across constraint conditions (i.e., using the Bartlett scores between the spaces). Finally, we tested whether there were significant rating differences across constraint conditions. To test this, we calculated mean ratings for each material and adjective pair across participants separately for each condition and calculated the distances between mean value (6 distances: *bare hand-open-fingered glove*, *bare hand-glove with rigid sensors*, *bare hand-full glove*, *open-fingered glove-glove with rigid sensors, open-fingered glove-full glove*, and *glove with rigid sensors-full glove* for each of the 150 material-adjective ratings). We then resampled the data using a Monte Carlo method (Efron, 1979) by creating 10.000 rating distances and used a 95% cut off for this distribution. Lastly, using the Binomial distribution, we statistically tested whether there was a significant pattern among the determined distances.

4.3. Results

4.3.1. Consistency across and within the participants

We checked internal consistency across participants by correlating responses from each participant (i.e., 150 values per condition) with the others, separately for each condition. Each material was evaluated once for each adjective across four different conditions by 23 participants.

All correlations across participants were positively correlated at $p < .01$ level with an average correlation of 0.63.

4.3.2. PCAs on bare hand, open-fingered glove, glove with rigid sensors, and full glove rating data

The high correlations between participants suggested that they all used similar criteria to judge the materials, according to the different adjectives. We next performed PCA separately on the ratings for each constraint condition. The dataset for each condition consisted of ratings for each material and adjective pair for every participant (10 materials x 15 adjectives x 23 participants) and it was submitted to a covariance based PCA with Varimax rotation. Before the PCA, we calculated the KMO and Bartlett's test of sphericity in order to check the suitability of the data for PCA. The KMO criterion was .82, .85, .84, and .80 for the *bare hand*, *open-fingered glove*, *glove with rigid sensors*, and *full glove* conditions, respectively, indicating meritorious suitability for PCA [9]. Also, Bartlett's test of sphericity was significant for all conditions ($p < .01$): χ^2 (105) =1878.95, χ^2 (105) =2079.62, χ^2 (105) =2251.03, and χ^2 (105) =1908.87, confirming that the observed correlations across adjectives are meaningful. We forced PCA to extract four dimensions in the *open-fingered glove* and *glove with rigid sensors* conditions, where the algorithm originally extracted three dimensions by default. The reason behind this was that, in both conditions, eigenvalues for the fourth dimension were just below the cutoff for extraction (extraction cutoff 100/15: 6.6, eigen values: 6.03 for open-fingered glove and 6.56 for glove with rigid sensors). Also, although there were small differences between the number of extracted components across conditions, the general pattern was very similar.

The PCA for the *bare hand* condition extracted four components, which explained 72.26% of the variance. The first component, which we called *viscosity*, had high loadings (>40% of mean variance: .87 or higher load on this factor than on others) from *moist*, *sticky*, *smooth*, and *rough* (21.9 % explained variance). The second component, named *granularity*, had high loadings from *granular*, *powdery*, and *sandy* (20.9% explained variance). The third component, *surface softness*, had high loadings of *fluffy*, *velvety*, *soft*, *hairy*, and *hard* (20.3% explained variance). The last component was *deformability* with high loadings from *elastic* and *inflexible* (9.1% explained variance).

The PCA for the *open-fingered glove* condition extracted four components, explaining 74.46% of the variance. The first component accounted for 23.90% of the variance with high loadings (>40% of mean variance: .87 or higher load on this factor than on others) of *moist*, *sticky*, *wobbly*, *smooth, and rough*, and we called it *viscosity*. The second component, accounting for 20.93% of the variance, was named *surface softness*, and had high loadings of *fluffy*, *soft*, *velvety*, *hairy*, and *hard*. The third component, accounting for 21.23% of the variance, was called *granularity*, and had high loadings of *sandy, powdery,* and *granular*. The last component accounted for 8.40% of the variance with high loadings of *inflexible* and *elastic* and was called *deformability*.

The PCA for the *glove with rigid sensors* condition extracted four components which explained 75.54% of the variance. The first component, which we called *granularity* (23.10% explained variance) had high loadings (>40% of mean variance: .86 or higher load on this factor than on others) of *sandy*, *powdery*, and *granular*. The second component, named *viscosity*, had the loadings of *moist*, *sticky*, *wobbly*, and *smooth* (22.37% explained variance). The third component, *surface softness* (21.04% explained variance), had high loadings of *fluffy*, *soft*, *hairy*, *velvety*, *hard*, and *rough*. The last component was *deformability* (8.67% explained variance) with high loadings of *inflexible* and *elastic.*

The PCA for the *full glove* condition extracted four components, explaining 71.48% of the variance. The first component accounted for 21.38% of the variance with high loadings (>40% of mean variance: .84 or load higher on a factor than on others) of *moist*, *wobbly*, *sticky*, and *smooth*, and we called it, *viscosity*. The second component, named *granularity*, accounted for 22.72% of the variance and had high loadings of *sandy*, *powdery*, *granular*, and *rough*. The third component accounted for 18.17% of the variance with the loadings of *fluffy*, *soft*, *velvety*, *hairy*, and *hard*, and it was called *surface softness*. The last component accounted for 9.20% of the variance and was called *deformability* with the loadings of *elastic* and *inflexible*.

Adjective and material loadings across conditions showed a very similar pattern (see PCA adjective loadings and Figure 4.3). In order to further assess the similarity between PCAs, we conducted a Procrustes analysis on the Bartlett values of each material across four common components (*surface softness, granularity, viscosity).* It was performed using the Procrustes MATLAB function (Baumgartner et al., 2013; Vardar et al., 2019). The functions fit one multi-dimensional space to another using linear transformations (translation, orthogonal rotation, and reflection). The output gives a Procrustes value which is the distance between spaces defined as the sum of the squared discrepancies between the transformed values in the two spaces: lower values indicate better fit between spaces. The values were quite low: .05 (*bare hand* vs. *glove*), .01 (*bare hand* vs. *open-fingered glove*), .01 (*bare hand* vs. *glove with rigid sensors*), .06 (*open-fingered glove* vs. *full glove*), .01 (*open-fingered glove* vs. *glove with rigid sensors*), and .04 (*glove with rigid sensors* vs. *full glove*). Considering the similarity between the PCAs and the low distances from the Procrustes analysis, we proceeded with a combined PCA, including values from all four constraint conditions. This allowed us to make more fine-grained comparisons between the four constraint conditions.

4.3.3. Combined PCA for bare hand, open-fingered glove, glove with rigid sensors, and full glove rating data

Based on the results from the previous section, we performed a combined PCA on the ratings of all constraint conditions. The dataset consisted of the ratings from the all constrain conditions (10 materials x 19 adjectives x 23 participants x 4 conditions) which was submitted to a covariance-based PCA with Varimax rotation. The KMO value (.84) and the Bartlett test (χ^2 (105) = 7930.41, p <.01) suggested that the observed correlations were meaningful, and that combined rating data was suitable for PCA. We extracted three components using a covariance based PCA with varimax rotation (Table 4.1.). The first component explained 23.82% of the variance with high loadings (>40% of mean variance: .86 or higher load on this factor than on others) of *sandy*, *powdery*, *granular*, *inflexible*, and *elastic*. We named it, *granularity*. The second

TABLE 4.1. Rotated adjective loadings from the combined PCA analysis (bare hand, open-fingered glove, glove with rigid sensors, and glove conditions). Components determined based on the adjectives that load highly (>40% of mean variance: .86) and load higher on a specific factor than on others. Bold if both criteria are fulfilled, italic if loading is only maximal for adjective. Lighter colors show negative loadings, darker colors show positive loadings.

Adjective	Granularity	Viscosity	Surface softness
Explained variance	23.82%	22.68%	19.81%
Sandy	**1.38**	-0.32	-0.19
Powdery	**1.13**	-0.11	0.03
Granular	**1.20**	-0.41	-0.33
Inflexible	*0.75*	0.06	-0.19
Elastic	*-0.69*	0.20	0.23
Moist	-0.12	**1.35**	-0.21
Sticky	0.00	**1.11**	-0.16
Wobbly	-0.23	**0.91**	0.25
Smooth	-0.31	**0.88**	0.23
Rough	0.62	*-0.84*	-0.64
Fluffy	-0.30	-0.23	**1.30**
Soft	-0.32	0.36	**1.02**
Hairy	-0.28	-0.48	**0.95**
Velvety	0.04	0.17	*0.82*
Hard	0.34	-0.42	*-0.58*

component, called *viscosity*, accounted for 22.68% of the variance with high loadings of *moist*, *sticky*, *wobbly*, *smooth*, and *rough*. The last component explained 19.81% of the variance with high loadings of *fluffy*, *hairy*, *soft*, *velvety*, and *hard*, and we labelled it *surface softness*.

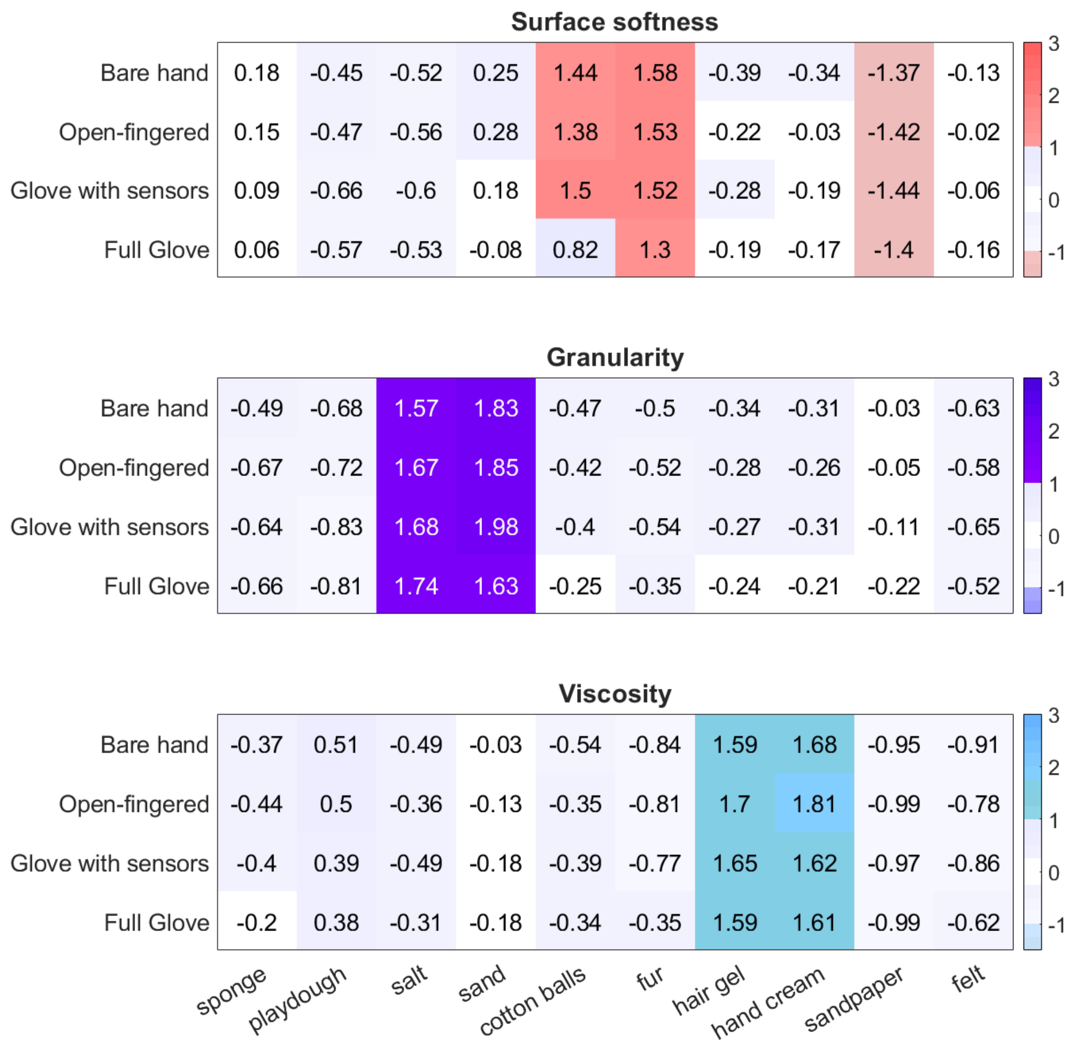

Figure 4.3. Rotated Bartlett scores (of materials) in surface softness, granularity, and viscosity dimensions across *bare hand*, *open-fingered glove*, *glove with rigid sensors*, and *full glove* conditions, respectively. Saturated colors indicate positive loadings and desaturated colors represent negative loadings. Light gray and white areas indicate that loadings were larger than -1 or smaller than 1 SD.

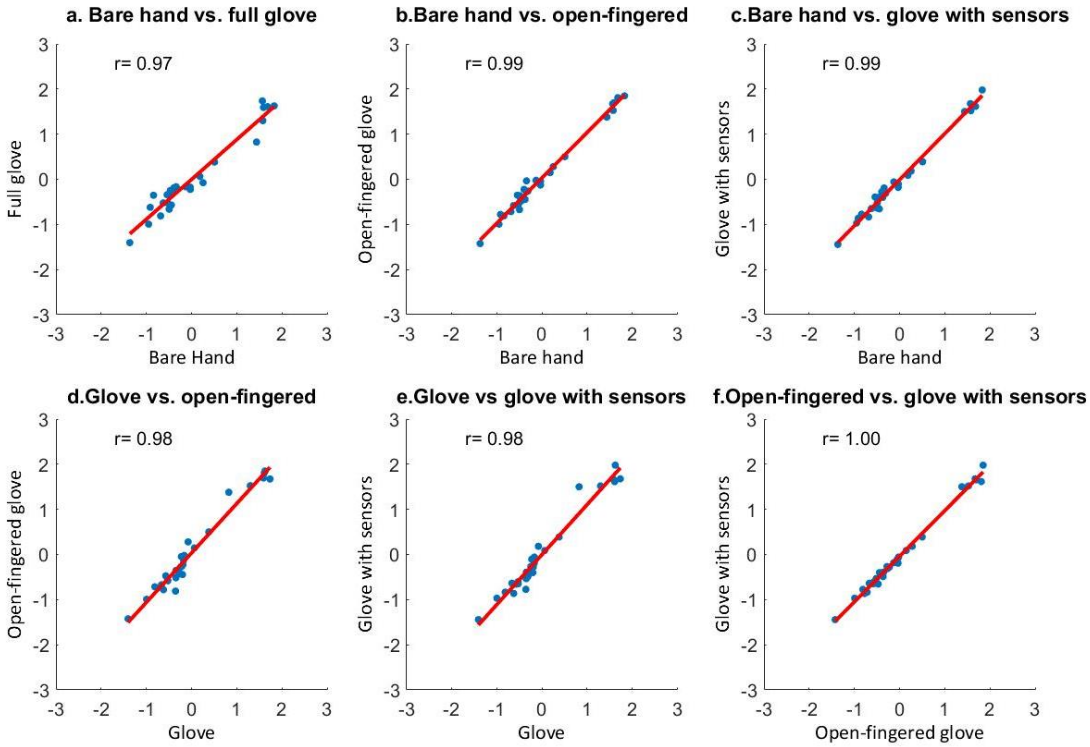

Figure 4.4. Correlation between Bartlett scores (material scores) of *bare hand* and *full glove* (a), *bare hand* and *open-fingered glove* (b), *bare hand* and *glove with rigid sensors* (c), *full glove* and *open-fingered glove* (d), *full glove* and *glove with rigid sensors* (e), *open-fingered glove* and *glove with rigid sensors* (f) conditions. Blue lines represent the trendlines.

4.3.4. Correlation between conditions

To investigate similarities between the *bare hand*, *open-fingered glove*, *glove with rigid sensors*, and *full glove* conditions, we correlated Bartlett scores (i.e., material scores) from each space (i.e., from each of the three softness dimensions) with one another (Figure 4.4). Note that values for this analysis and the following analyses were taken from the combined PCA. Overall, Fig. 4 shows that correlations between the spaces were strong. The strongest correlation was for the *open-fingered glove* and *glove with rigid sensors* conditions (r =.997, p <.01), followed by the *bare hand* and *open-fingered glove* (r =.99, p <.01) conditions. Next, came the *bare hand* and *glove with rigid sensors* (r =.99, p <.01) conditions, followed by the *full glove* and *open-fingered* *glove* (r =.98, p <.01) conditions. After that was the *full glove* and *glove with rigid sensors* (r =.98, p <.01) conditions. Lastly, the least strong correlation was between the *bare hand* and *full glove* conditions (r =.97, p <.01).

4.3.5. Rating differences across conditions

Overall, we had 39 values exceeding the cut off value determined by the Binomial/Monte-Carlo procedure mentioned in the Methods. None of these values belong to the comparison between the *open-fingered glove* and *glove with rigid sensors* conditions. We also observed a general pattern where the *full glove* condition differed from the others. We then tested whether the involvement of the *full glove* condition was significantly more frequent that the other conditions (calculated for 39 distances using the Binomial distribution; smaller frequency distances used as a

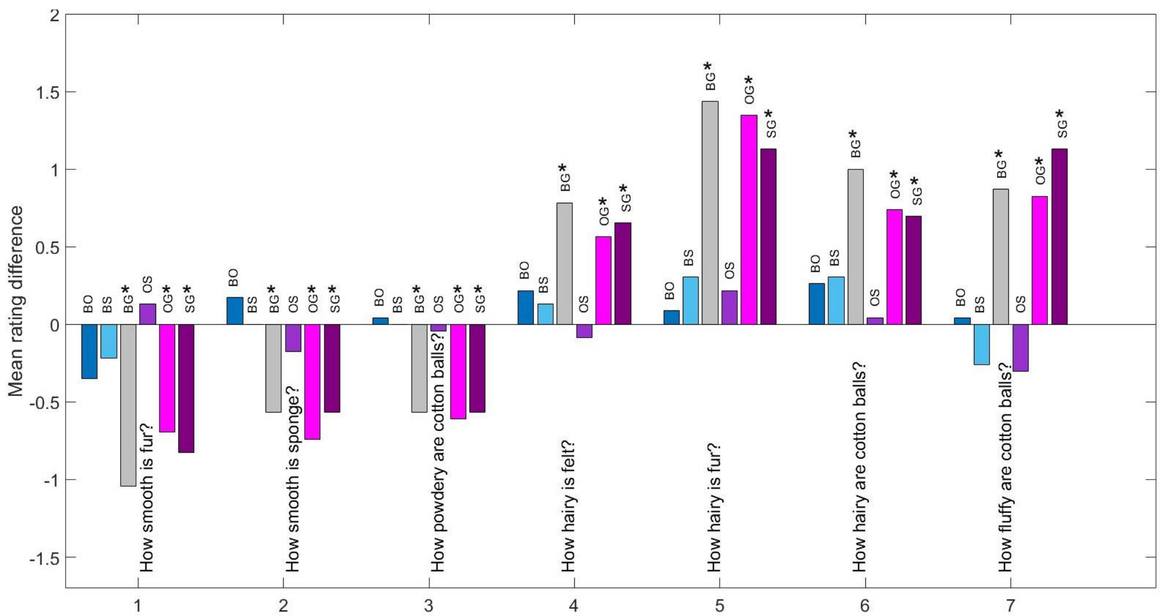

Figure 4.5. Mean rating differences between the *bare hand*, *open-fingered glove*, *glove with rigid sensors*, and *full glove* conditions. BO, BS, BG, OS, OG, and SG refer to differences in rating. BO: *bare hand* vs *open-fingered glove* (dark blue), BS: *bare hand* vs *glove with rigid sensors* (light blue), BG: *bare hand* vs *full glove* (gray), OS: *open-fingered glove* vs *glove with rigid sensors* (violet), OG: *open-fingered glove* vs *full glove* (magenta), SG: *glove with rigid sensors* vs *full glove* (purple). Asterisk shows the mean differences bigger than 95% percent.

baseline). We found that 87.18% of the comparisons involved the *full glove* condition, which was significant. Here, we have focused on the material-adjective pairs where the distances in the *full glove* condition differed from the rest of the conditions, because of space limitations. In a bar graph, we represent these 7 cases (Figure 4.5). The y-axis shows material and adjective pairs. On the x-axis, we plot the mean rating difference between pairs of conditions. Positive values indicate that participants rated an adjective as applying more to a given material in one condition (e.g., hairy applies to felt more in the *bare hand* than in the *full glove* condition), while a negative value means an adjective applies more in the other condition (e.g., smooth applies to fur less in the *bare hand* condition than *open-fingered glove* condition).

4.4. Discussion

We investigated whether restrictions with a full glove, open-fingered glove, or a glove with rigid sensors in free exploration affect perceived softness compared to a bare hand. We found that judgments in all conditions were strongly correlated with each other, meaning that in general, perceived softness for different dimensions was not affected by the constraints on exploration implemented here. However, when we looked at the rating differences of the people on a material-adjective level, we found some differences, especially between the full glove and other conditions. Thus, we replicated previous findings by showing that softness is a multidimensional construct with the dimensions of viscosity, granularity, and surface softness (Cavdan et al., 2019; Cavdan et al., 2021), which confirms the multidimensionality of perceived softness. Here, we did not have the deformability dimension, which might be due to the number of reduced materials used in the current study.

When free exploration was restricted using a glove, an open-fingered glove, or a glove with rigid sensors, the perception of different softness dimensions was not changed compared to the bare hand condition. We determined this by looking at the similarities in PCA results and the strong correlations between material values across conditions. Although the participants might not have been able to gather detailed information about a material because of restrictions, they still might have access to a material's coarse information (i.e., size and shape (Lederman & Klatzky, 2004)). Even with the hand completely covered (i.e., full glove), participants were able to obtain and evaluate different dimensions of softness.

Furthermore, the most important difference between the open-fingered glove/glove with rigid sensors and bare hand conditions was that the participants could also get information from the palms and proximal fingers with bare hands. However, the similarity between these two glove conditions and the bare hand condition suggests that people might be in general relying on the information that they gathered from their fingertips. This is in line with previous research that shows the palm is the least used contact area in the hand (Gonzalez et al., 2014).

In daily life, we not only decide between different categories, but we also make decisions within one object category. For instance, when deciding on which avocado is more edible, we apply pressure to a couple of avocados before deciding on which one to buy. It seems as if the task in our experiment was one in which participants could evaluate material properties using coarse information of a material but not with finely-detailed information. This suggests that if participants had been given a finer judgement task (e.g., distinguishing two types of sand of differing granularity), judgements in the bare hand condition might show higher discrimination ability on the part of the subjects than in the full glove condition. Future research can investigate this point using similar restriction conditions as in the current study and by presenting participants different degrees of soft materials from the same category with a discrimination task. Additionally, wearing a glove might reduce the number of hand movements used during exploration. Thus, people might adapt exploratory movements depending on the condition they are in. This point can be tested by decoding hand movements as in (Cavdan et al., 2019; Cavdan et al., 2021).

To conclude, it seems that perceiving surface softness requires information from the fingertips that can be reduced by covering the fingertips. On the other hand, perceived dimensions of haptic softness are not affected by restrictions on free exploration. This might mean that the coarse information of an object (e.g., whether a sponge is soft) might contribute most to the perception of soft materials, rather than fine information, such as when deciding on which hand cream is more viscous.

5. From Hate to Love: How Learning Can Change Affective Responses to Touched Materials

A similar version of this manuscript has been published as: Müge Cavdan, Alexander Freund, Anna-Klara Trieschmann, Katja Doerschner, & Knut Drewing (2020). From Hate to Love: How Learning Can Change Affective Responses to Touched Materials. In: Nisky I., Hartcher-O'Brien J., Wiertlewski M., Smeets J. (eds) Haptics: Science, Technology, Applications. EuroHaptics 2020. Lecture Notes in Computer Science, vol 12272. Springer, Cham.

People display systematic affective reactions to specific properties of touched materials. For example, granular materials such as fine sand feel pleasant, while rough materials feel unpleasant. We wondered how far such relationships between sensory material properties and affective responses can be changed by learning. Manipulations in the present experiment aimed at unlearning the previously observed negative relationship between roughness and valence and the positive one between granularity and valence. In the learning phase, participants haptically explored materials that are either very rough or very fine-grained while they simultaneously watched positive or negative stimuli, respectively, from the International Affective Picture System (IAPS). A control group did not interact with granular or rough materials during the learning phase. In the experimental phase, participants rated a representative diverse set of 28 materials according to twelve affective adjectives. We found a significantly weaker relationship between granularity and valence in the experimental group compared to the control group, whereas roughness-valence correlations did not differ between groups. That is, the valence of granular materials was unlearned (i.e., to modify the existing valence of granular materials) but not that of rough materials. These points to differences in the strength of perceptuo-affective relations, which we discuss in terms of hard-wired versus learned connections.

5.1. Introduction

We constantly interact with various materials like plastic, fabric, or metal. Haptic perceptual properties of materials have been summarized by five different dimensions (Okamoto et al., 2013) that are softness (but cf. Cavdan et al., 2019), warmness, micro- and macro roughness, friction, and stickiness. In addition to the sensory properties that we experience while haptically exploring a material, we often also have an initial affective reaction to it. Moreover, the affective reactions that a material elicits might also influence the duration of our haptic interactions. For example, soft and smooth materials, which cause more pleasant feelings than rough and sticky materials (Essick et al., 2010; Ripin & Lazarsfeld, 1937; Klöcker et al., 2013; Klöcker et al., 2012; Ramachandran & Brang, 2008) might be explored longer.

Previous research on the semantic structure of affective experiences postulates three basic affective dimensions (Russel & Mehrabian, 1977): valence, *arousal*, and *dominance,* where each dimension has two opposite poles (Osgood, 1952): arousal ranges from a very calm state and sleepiness (low) to vigilance, which is accompanied by excitement (high). Valence is a continuum from negative to positive and dominance ranges from dominant to submissive. Most of the research in haptic perception has focused on the connection between pleasantness (which can be equated with valence) and the perception of sensory dimensions. One key finding has been that smooth and soft materials are related to more pleasant feelings than rough materials (Guest et al., 2010), and that the rougher a material is rated, the more unpleasant it feels (Guest et al., 2010). In a more recent study (Drewing et al., 2018), all three basic affective dimensions and their relationship with materials' sensory characteristics have been systematically investigated: Drewing et al. (2018) used a free exploration paradigm to study the sensory and affective spaces in haptics and tested the generalizability of their results to different participant groups. They found that arousal was related to the amount of perceived fluidity, that higher dominance as associated with increases in perceived heaviness and decreases in deformability, and that greater positive valence was associated with increased granularity and decreased roughness.

It is currently unknown to what extent such perceptuo-affective connections are due to learning experiences and to what extent they are hard-wired, innate mechanisms. Here we investigated directly whether existing relationships between sensory material properties and affective responses can be unlearned, and whether the extent of unlearning depends on the specific perceptuo-sensory relation, for two haptic perceptual dimensions: granularity and roughness. We speculate that hard-wired connections should be more resistant to unlearning than learned ones.

We ran a classical conditioning study that consisted of two phases: learning and experimental phases with two groups each (experimental and control). In the learning phase, participants haptically explored selected materials while watching affective images: In the experimental group rough materials were combined with positive images, granular materials with negative images and distractor materials with neutral images. In the control group participants learned instead associations of fibrous and fluid materials with arousal, which were however not subject of this paper and will not be further discussed. In the experimental phase, participants rated a representative set of 28 materials for 12 affective adjectives. We calculated perceptuo-affective correlations for valence-roughness and valence-granularity relationships per group and compared these correlations between groups. Lower correlations for the participants in the experimental group would indicate an unlearning of the relationship between valence and the respective perceptual dimension.

5.2. Methods

5.2.1. Participants

Sixty-six students (9 males; age 18-34 years, mean: 23.5 years) from Giessen University participated in our study. Four were excluded from analysis due to misunderstanding the task, technical error, or an increased threshold in the two-point touch discrimination (>3 mm at index finger). All participants were naïve to the aim of the experiment, spoke German at native-speaker level, and none reported relevant sensory, or motor impairments. All procedures were in accordance with the Declaration of Helsinki (2008), and participants provided written informed consent prior to the study.

5.2.2. Setup, material, and adjectives

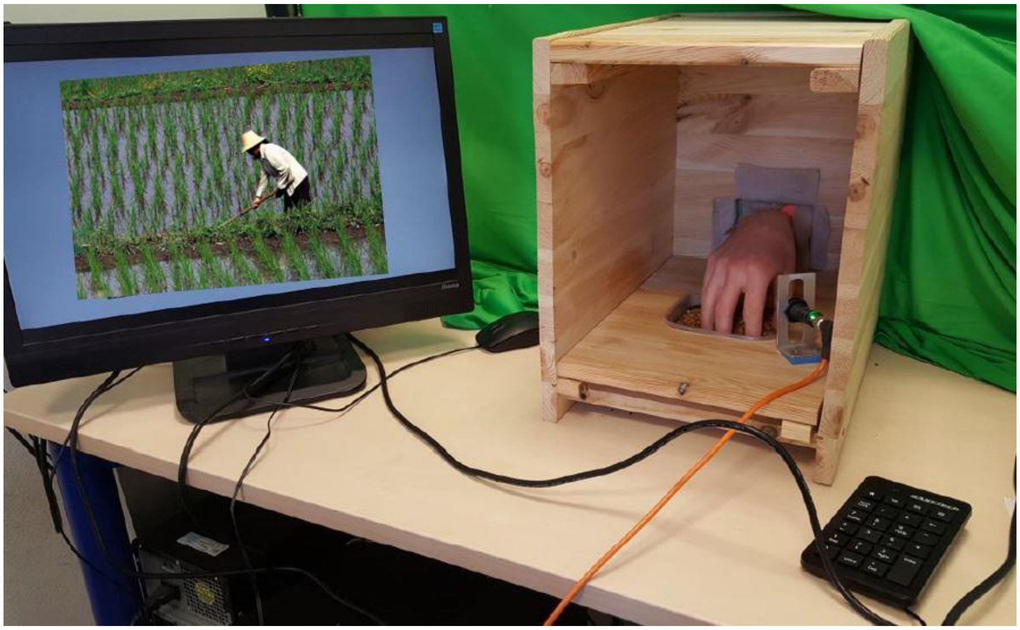

Figure 5.1. Experimental setup from the experimenter's viewpoint.

Participants sat at a table in front of a big wooden box with a hand opening. Materials were presented in the box (see Figure 5.1). Participants reached the materials through the hand opening, which was covered with linen to hinder participants to look inside the box. On a monitor (viewing distance about 60 cm) we presented images (visual angle 14.2°) and adjectives to the participant. Earplugs and active noise cancelling headphones (Beyerdynamic DT770 PRO, 30 Ohm) blocked the noises that can occur from exploring the materials. All materials were presented in 16 x 16 cm plastic containers embedded in the bottom of the box. A light sensor in the box signaled when the participant's hand was on the front edge of the container, allowing to start picture presentation simultaneously to haptic exploration. Participants gave responses using a keyboard. The experimenter sat on the other side of the table in order to exchange materials guided by information presented on another monitor.

For the learning part of the experimental group, we selected materials from (Drewing et al., 2018) which had a high factor value on one of the target sensory dimensions (either granularity or roughness) but did not show high factor values in any of the other dimensions (fluidity, fibrousness, heaviness, deformability). Bark and sandpaper were selected for roughness, and salt and lentils for granularity. In the control group other materials were used (jute, wadding, water, shaving foam). Additionally, for both groups (experimental and control) we added four distractor materials, which did not have high factor values on the manipulated dimensions: cork, chalk, paper, and polystyrene. We also obtained the sensory and affective adjectives from (Drewing et al., 2018); one to two representative adjectives per sensory dimension (rough, granular, moist, fluffy, heavy, and light, deformable, and hard). In the learning phase, sensory ratings served to draw the participant's attention to the materials.

For establishing affective-sensory associations we used images from the International Affective Picture Systems (IAPS). The IAPS database includes 1196 colorful images of various semantic contents, that have been rated according to valence, and arousal (Bradley et al., 2007; Lang et al., 2008). For the experimental group, we selected sixteen images with high negative valence (< 2.5) and sixteen images with high positive valence (> 7.5), and as diverse content as possible (excluding drastic injury images). For the control group, we used images with high or low arousal instead. We also selected 32 distractor images, which have average valence and arousal values (between 4.5 and 5.5).

In the experimental phase, participants rated 28 materials (plastic, wrapping foil, aluminum foil, fur, pebbles, playdough, silicon, paper, styrofoam, paper, sandpaper, velvet, jute, silicon, stone, bark, flour, metal, cork, polish stone, oil, shaving foam, soil, hay, chalk, salt, lentil). We assessed affective responses via adjectives and selected four high loading adjectives per affective dimension: *valence* (pleasant, relaxing, enjoyable, and pleasurable), *arousal (*exciting, boring, arousing, and attractive) and *dominance* (dominant, powerful, weak, and enormous/tremendous).

5.2.3. Design and procedure

Participants were randomly assigned to either the experimental or the control group. In the learning phase of the experimental group, we coupled the exploration of the two very rough materials with positive images and the granular materials with negative images, in order to manipulate valence. In the control group, different materials were explored and coupled with different images.

The learning phase consisted of 64 trials: in the experimental group, each of the two granular materials was presented eight times coupled with one of the 16 negative images, and each of the two rough materials was coupled 8 times with one of the positive images. Also, each of the four distractor materials (cork, chalk, polystyrene, and paper) was presented eight times with a distractor image. Both, the assignment of corresponding images to materials and the order of presentation, were random.

In each trial of the learning phase (Figure 5.2), an initial beep sound signaled the participant to insert the hand in the box and to start exploring the material. When participant's hand started the exploration, an image was displayed on the screen. Participants explored the materials while looking at the images for five seconds. Another beep sound signaled participants to end the exploration, and a randomly chosen sensory adjective appeared on the screen. Participants rated how much the adjective applied to the material (1*: not at all*, 4: *maybe,* 7: *very*) using a keyboard. Finally, a multiple-choice question about the main content of the image was posed. The experimenter exchanged the stimuli between trials. In total, the learning phase took about 30 min.

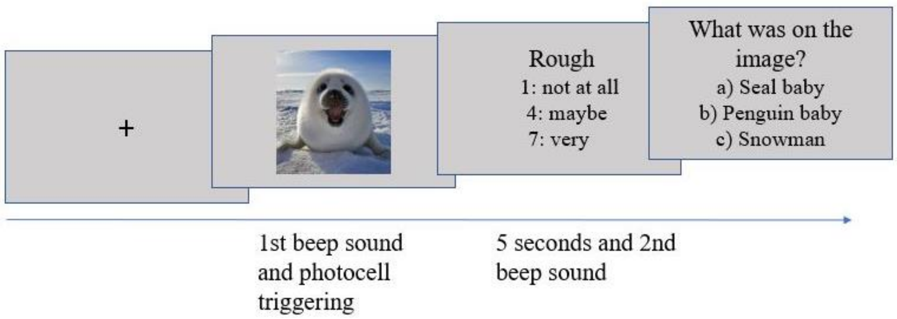

Figure 5.1. Time course of one trial of the learning phase.

The experimental phase consisted of 336 trials (28 materials x 12 adjectives). Each trial started with a fixation cross on the screen (Figure 5.2). Then participants reached in the box with their dominant hands and explored the material. During exploration each of the 12 affective adjectives appeared on the screen (in random order), and participants had to rate how much each adjective applied to the material (1-7). The hand was retracted, and the material exchanged after all twelve adjectives were evaluated. The total duration of the experiment including learning phase, instructions, preparation, pauses for cleaning hands and debriefing was about 2 - 2.5 hours.

5.2.4. Data analysis

We first assessed the number of correct responses from the multiple-choice questions of the learning phase. With an average of 96.2% correct (individual minimum: 84.4%), we could verify that all participants had attended to the images as they should. Next, we used the affective ratings from the experimental phase in a covariance-based principal component analysis (PCA) with Varimax-rotation (for all adjective ratings across all materials and participants) in order to extract underlying affective dimensions. Before doing so, we assessed whether the PCA was suitable by a) checking the consistency across participants by calculating Cronbach's alpha for each affective adjective (separately for experimental and control group), b) computing the Kaiser-Meyer-Olkin (KMO) criterion, c) using Bartlett's test of sphericity (Drewing et al., 2018).

Lastly, in order to test a potential unlearning of the perceptuo-affective relationships valence-roughness and valence-granularity, we determined material-specific individual factor values of the valence dimension. We calculated individual correlations of these values with previously observed average granularity and roughness values across materials (taken from Exp. 2 in Drewing et al., 2018), and used two independent samples t-tests in order to compare the two perceptuo-affective Fisher-z transformed correlations of experimental and control group.

5.3. Results

5.3.1. PCA on Affective Dimensions

Cronbach's alpha was higher than .80 per adjective and participant group, indicating good consistency between participants. Bartlett's test of sphericity was statistically significant, $\chi2(66, N=28) = 12868.897$, $p<.001$, and the KMO value, which has a range from 0 -1, was 0.86 (Cerny & Kaiser, 1977). Given these results we proceeded with the PCA.

The PCA extracted three components according to the Kaiser criterion, explaining 73.1% of the variance in total. After the varimax-rotation, the first component explained 31.8% variance with the highest component loads obtained from the adjectives pleasant (score: 1.8), relaxing (1.8), enjoyable (1.5), and pleasurable (1.8). Thus, we identified this component as *valence*. The second component explained 22.4% variance with high loads from adjectives dominant (1.6), powerful (1.6), weak (-1.1), and enormous/tremendous (1.6); consequently, we called this component dominance. The last component explained 18.9% variance with high loads from exciting (1.4), boring (1.5), arousing (0.7), and attention-attracting (1.5), and therefore we labeled it arousal. All other component loads of any adjective had an absolute value below 0.7 and where thus not considered in the interpretation.

5.3.2. Learning effects on materials

For the control group (N=30), correlations between roughness and valence, r = -. 37, p <.001 and granularity and valence, r = .25, p <.001 were statistically significant after Bonferroni correction, confirming the basic perceptuo-affective relations previously observed in (Drewing et al., 2018). In order to test the effect of unlearning perceptuo-affective relationship, we compared the Fisher-z-transformed correlations of the two groups (Figure 5.3).

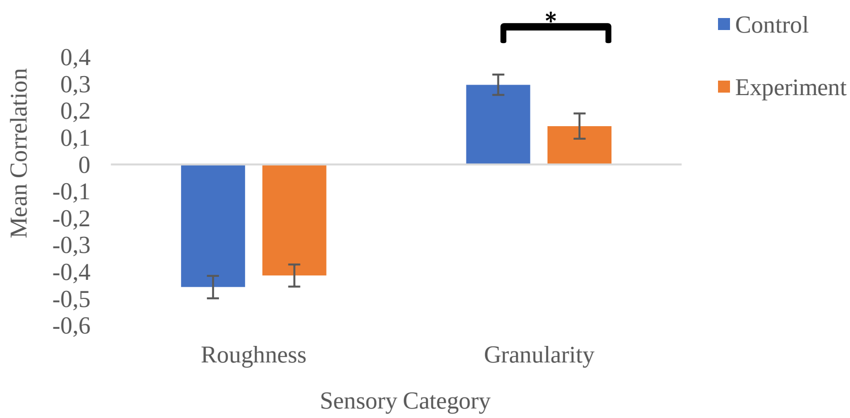

Figure 5.3. Relationship between sensory category and valence for experimental (orange) and control group (blue). It shows mean correlations (inverse of average Fisher z-transforms) as a function of sensory category (roughness and granularity). Error bars show 1± standard errors (*Significant *p* < .05 level).

There was not a statistically significant difference between experimental (*M*=-.41, *SD*= .21) and control (*M*= -.46, *SD*=.23) groups, *t* (60) = .763, *p*=.449 for the valence-roughness correlation. However, there was a statistically significant difference between control (*M*= .30, *SD*= .23) and experiment (*M*=.14, *SD*=.26) groups, *t* (60) = -2.461, *p*=.017 for the valence-granular correlation.

5.4. Discussion

People experience rougher materials as more unpleasant, and more granular materials as more pleasant (Drewing et al., 2018). Here we investigated whether brief learning experiences can influence the affective assessments of these two material properties. Our aim was to modify previously found affective responses towards granular and rough materials, and we found, that the perceptuo-affective correlation between granularity and valence was lowered through learning in the experimental group compared to control group. However, the valence-roughness relation was not significantly different in experimental and control group, suggesting that this connection could not be unlearned. We suggest that these results demonstrate different strengths in the perceptuo-affective connections, which relate to the degree to which connections are learned during lifetime vs being evolutionary prepared to serve a biological function.

Studies on fear conditioning suggest that some classes of stimuli are phylogenetically prepared to be associated with fear responses, while others can be hardly learned. For example, it has been shown that lab-reared monkeys easily acquire fear of snakes by observing videos of the fear that other monkeys had shown - even if they had never seen snakes before in their lives (Cook & Mineka, 1990). When these videos were reproduced to create similar fear against toy snakes, crocodiles, flowers, and rabbits, lab-reared monkeys showed fear against snakes and crocodiles, but not flowers and rabbits (Cook & Mineka, 1991). Because these monkeys had never been exposed to the stimuli before, this can be taken as evidence for a phylogenetic basis of selective learning. Furthermore, in humans, researchers observed superior fear conditioning to snakes when compared to guns with loud noises (Cook et al., 1986), which also supports the idea of phylogenetically based associations for snakes and fear.

Natural rough materials, such as rocks or barks, could be harmful because of their surface structure they could potentially break the skin. Therefore, an association of those materials with feelings of unpleasantness could be prepared in our nervous system, which would make it difficult to associate those materials with positive valence. In contrast, granular materials that are present in our environment such as sand, generally do usually not pose a danger. Thus, their associations with valence are probably not evolutionary driven. This might explain why we seem to be more flexible in associating granularity with positive or negative valence than associating roughness with positive valence. This flexibility is evident in our results since participants in the experimental group learned to associate granular materials with negative valence. We conclude that even brief learning experiences can change perceptuo-affective connections depending on the source and strength of the relationship. In the current case, the valence of granular materials was unlearned but not that of rough materials. This might mean that perceptuo-affective connections for granular materials are learned, yet for rough materials they might be hard-wired or at least prepared.

6. Discussion

Material perception is complex and a deeply rooted to our lives. With the four studies reported here, this thesis evidence for how material perception is shaped by material properties, physical constraints, agent's intentions, and affective response. The results of these studies support and extend the previous studies in the literature. Main conclusions of these results could be summarized in four points. First, we showed that softness instead of being equivalence of compliance is a multidimensional construct. Second, we compared the static and dynamic visual and haptic perception of softness. This yield potential application for online shopping. Third, we explored how material perception is affected by physical constraints in daily life applications. Finally, we found evidence suggesting the emotional associations of materials could stem from various sources.

6.1. Softness as a multidimensional construct

In the literature softness is equated to the compliance of materials. However, Dovencioglu et al. (2021) challenged this idea by showing that softness underlies various perceptual dimensions of materials. In study 1, we seek to replicate and more importantly explore how the materials, task, and their interaction modulate the EPs. We replicated the results of Dovencioglu et al. (2021), suggesting that the perceived softness consists of multiple dimensions which are viscosity, deformability, granularity, and furriness. We recorded the hand movements of the participants in each trial. These movements separately grouped based on the material and task combination of the trial. Then, these movements were subsequently categorized into EPs. We found that people adapt their hand movements depending on the material category (Dovencioglu et al., 2021), their purpose (Lederman & Klatzky, 1987), and the interaction between the two when perceiving different aspects softness haptically. Our results were further supported by a linear support vector machine trained on partial data which significantly predicted material categories from our EPs. The results yield complex interaction with material and task. For instance, with viscous materials pulling is used to judge deformability and viscosity, while it is used to judge deformability but not viscosity of furry materials. Therefore, not only material category and task but also their interaction determine the EPs. Some results were less intuitive. Participants tended to frequently rub materials independent of what it is they are touching or what it is they are judging. However, this EP is followed by other EPs which are associated with specific properties of materials, task, or interaction of both. In fact, we observed the usage of movement combinations (e.g., *run through* followed by *rotate* for granular materials) instead of the strict specialization of a single movement. These movement combinations might help people to gather the information optimized for the task and the material. Moreover, information gathering might be in a coarse to fine fashion. Continuing with granular materials, while *run through* might provide initial coarse information on density, weight, or viscosity of the grains, *rotate* might provide follow-up fine information about the size or shape of the grains. In other words, it appears that first EPs give coarser information while the followed-up EPs might provide finer information. Therefore, the exploration duration might influence how we perceive soft materials by touch. In short explorations only first EP might be used to optimize the information gain. This idea is in line with previous research (Klatzky & Lederman, 1999, Zoeller & Drewing, 2020) and could be addressed in future. In the current study, we focused on the perceived softness as a result of interaction with hand. However, our interaction with soft materials not only restricted to hands but also includes other body parts. Therefore, how the different dimensions of softness differ as a function of different body parts is an intriguing question.

The first study revealed a complex relationship between material and task for softness perception by touch. Vision is another modality for softness perception. There are at least two immediate questions comes to mind: “Are softness dimensions we observed in haptics also present in vision?” and “Does the multidimensional construct of softness affected by the availability of different cues (i.e., static vs. dynamic)?”. In Study 2, we have shown that humans estimate different softness properties of natural materials from haptics, dynamic, and static visual scenes similarly. However, a closer inspection to correlations of Bartlett scores of materials has shown that judgments from dynamic visual information are more similar to that from haptics than judgments from static visual information. High correspondence suggest that the senses generally calibrate each other well on material properties, albeit the information basis strongly differs. It also suggests that for the perception of the dynamic softness properties dynamic information play a particular role, which can be gathered in the haptic and the visual dynamic information condition. Particularly, for viscosity dimension, correlation between dynamic and haptic spaces was significantly stronger than between dynamic and static spaces. *Stress balls* show high loadings in *viscosity* dimension of haptic and dynamic visual compared to static visual space when looking at the Bartlett scores. Although *stress balls* were squishy and sticky to touch, without any dynamic information their shape do not convey these properties. Therefore, shape of the material might result in less viscous association in the visual system (Schmidt et al., 2017). This example highlights how important dynamic information is in some specific situations. This finding is especially important for online shopping. One particular challenge in online shopping as oppose to physical shopping is the lack of information other than visual and auditory. However, in physical shopping we often strive to touch objects like fabrics or fruits and lack of haptic information in online shopping causes difficulties in decision making. Thus, it is one of the key challenges of sector (Rodrigues et al. 2017) to provide haptic information. This is more true for soft materials like fabrics (e.g., velvet, wool) invites you to hands-on experience (Levin et al. 2005). Wijntjes et al. (2019) found that observing hand movements in real life improved material inference. Here we also suggest that by presenting right kind of dynamic visual information (i.e., movies), we can evoke similar perceptions as touching a material. Our results extend the findings by Wijntjes et al. (2019) showing, right kind of dynamic information would be more informative compared to static images when perceiving soft materials. The perspective of the viewer could be an important factor to convey more relatable and ecological. We often see materials from top while touching. The hand movement videos we have recorded from the left side of a person. Therefore, the strength of the current correspondences we reported between visual and haptic domains might differ at different viewing angles. This needs to be addressed in future studies.

To sum up, one of the most important contributions of the first two studies to the literature was showing that softness is not only composed of compliance of materials, but it is a multidimensional construct. Therefore, a better understanding of the perception of softness requires investigation of all other dimensions besides compliance (i.e., granularity, viscosity, and furriness). This should be considered especially when asking participants to make judgements about the softness of materials. Additionally, although dynamic and static visual information lead to similar percept, dynamic information seems to provide further information when perceiving softness.

6.2. How haptic constrain affect haptic perception of softness

Due to a number of reasons, we may not touch a material directly without a middle layer. Interacting with an object through an intermediate layer could alter our experience simply because sensation of the underlying material properties is impaired by the layer. In Study 3, we investigated how haptic constrains -full glove, open-fingered glove, and open fingered-glove with rigid sensors- affect haptic perception of softness. We found that all conditions were highly correlated with each other. This means that haptic constraints we implemented during exploration in general were not severe enough to alter the perceived dimensions of softness. Especially in terms of grip dynamics and AR research, understanding the effect of gloves itself which is attached to the tactile sensors is of great importance. General findings of the current study show that restrictions did not damage the general frame of different perceived softness dimensions. However, on a more detailed level, material-adjective interaction, we found *full glove* condition to be differed from the other conditions especially for the judgements on surface softness dimension. This is not unexpected considering that people most frequently use their fingertips to interact objects by touch compared to other parts of the hand (Gonzalez et al., 2014). This is a physiologically valid strategy: density of mechanoreceptors increases from palm to distal phalanx and fingertips are more sensitive to tactile information. Therefore, open-finger glove conditions might be closer to bare hands because most of the information was already available through fingertips.

In our experiment, participants evaluated various qualities of different materials. However, in daily life we make decisions within the same categories as well such as distinguishing which of the two t-shirt is softer to buy. When comparing two t-shirt we need to get a fine-tune information on surface characteristics. However, while evaluating the different qualities of a material, as in the method we used, relatively coarser information might have been sufficient for some tasks. However, when the task requires discriminating materials from the same category (e.g., distinguishing two different degrees of sand in granularity), then coarse information may not be enough. In such a task, a difference between full glove and bare hand conditions can potentially be observed. Such scenario would make the rendering of distinct materials from the same category in AR or mixed reality even more challenging. Therefore, further understanding the relationship between grain of information and various levels and types of physical constraint is an important step to create realistic tactile experiences.

6.3. The origin of perceptuo-affective relationships in haptics

Our experience with objects depends on physical properties of the materials as well as our perceptuo-affective relationship with them. Therefore, our affective response to a sensory property might determine how and how much we interact with the objects featuring that property. It can be argued that our affective response to a given haptic property could be innate or learnt at some point of our life. In the last study, we investigated how flexible is relationships between sensory properties and affective responses towards them to change. The degree of flexibility or rate of unlearning pre-existing relationship might depend on both the strength of the association as well as to the nature (learned or innate) of it. Participants in our study was able to unlearn valence association with the granular materials but not rough materials. We interpret these results as an indication showing different strengths in perceptuo-affective connections. Thus, some connection might be learned during lifetime while others might be already prepared already in our nervous system.

On potential shortcoming of the current experiment is limited sampling of materials. One could argue that the unlearning affect (also not unlearning) might only limited to the materials we have used in the current study. This should be further tested with other materials. However, some stimuli are phylogenetically prepared to be associated with fear as evidenced by fear conditioning studies. For instance, lab-reared monkeys presented fear against snakes even if they have never seen snakes before (Cook & Mineka, 1990). Thus, in humans, researchers observed superior fear conditioning to snakes when compared to guns with loud noises (Cook et al., 1986). Following the same reasoning, naturally rough materials like bark or rocks might be harmful because they could potentially break the skin because of their surface structure. As a result, because of survival associations, unpleasant feelings towards rough material might be already prepared in our nervous system. However, this might not be the case for pleasant materials like sand which do not usually pose a danger. Therefore, this could imply that while we can modify the positive relationship, this might not be possible for the negative relationships. Therefore, it is needed to establish whether flexibility of perceptuo-affective associations is depends on pleasantness, specific perceptual dimension, innateness, or multiple factors.

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Supplementary Information

Supplementary Methods 1

Summary of selected exploratory movements from Dovencioglu et al., 2020 and Cavdan et al., 2019:

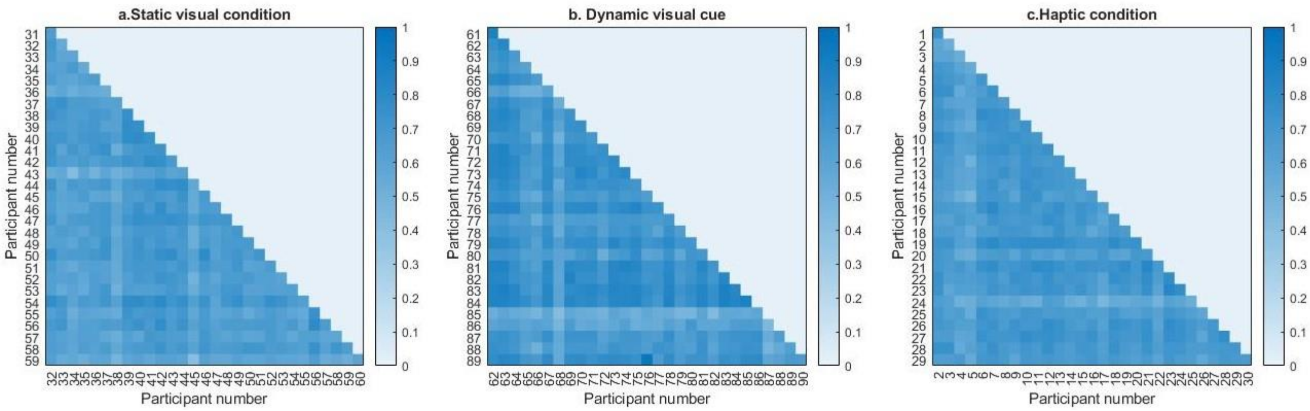
1. Run through: "Picking up some parts/portion of the material and letting them trickle through the fingers."

2. Rotate: "Lifting parts of the material to move and turn its boundaries typically inside the finger(tip)s."

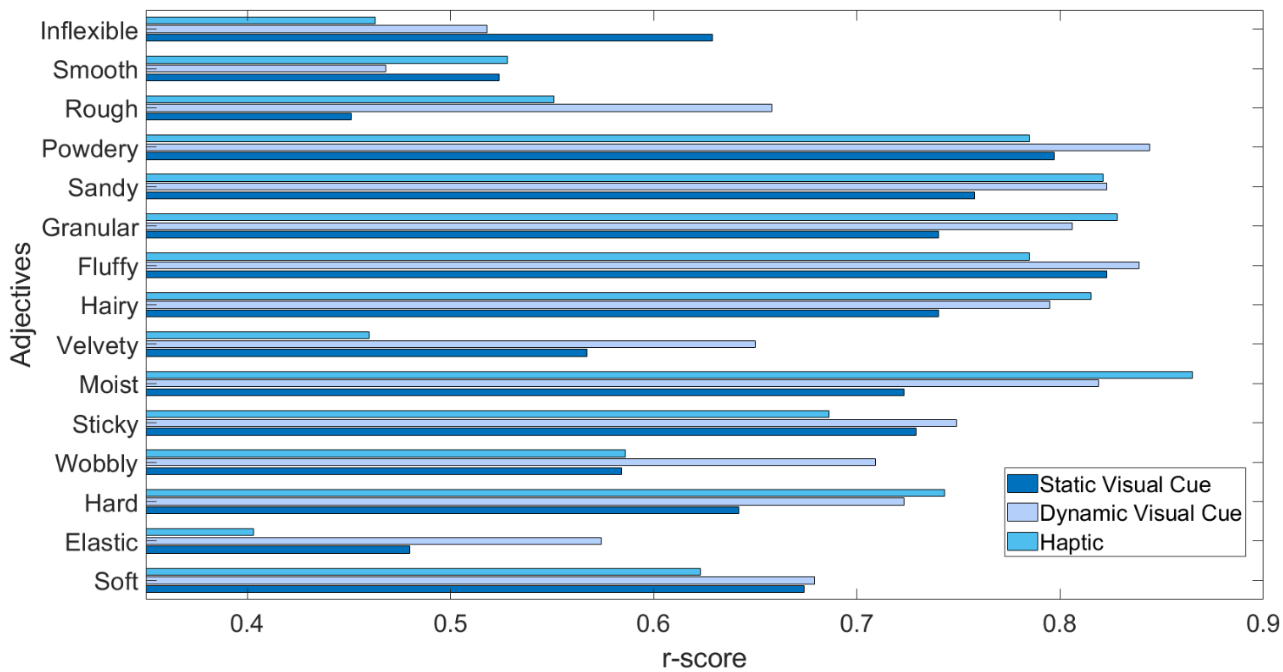
3. Rub: "Applying torque or lateral force with varied pressure levels, sometimes sweeping materials between index and thumb fingers or forcefully stroking material with the thumb while poising the object with the other fingers."

4. Pull: "Stretching a part of the material by moving fingers or separating them from each other."

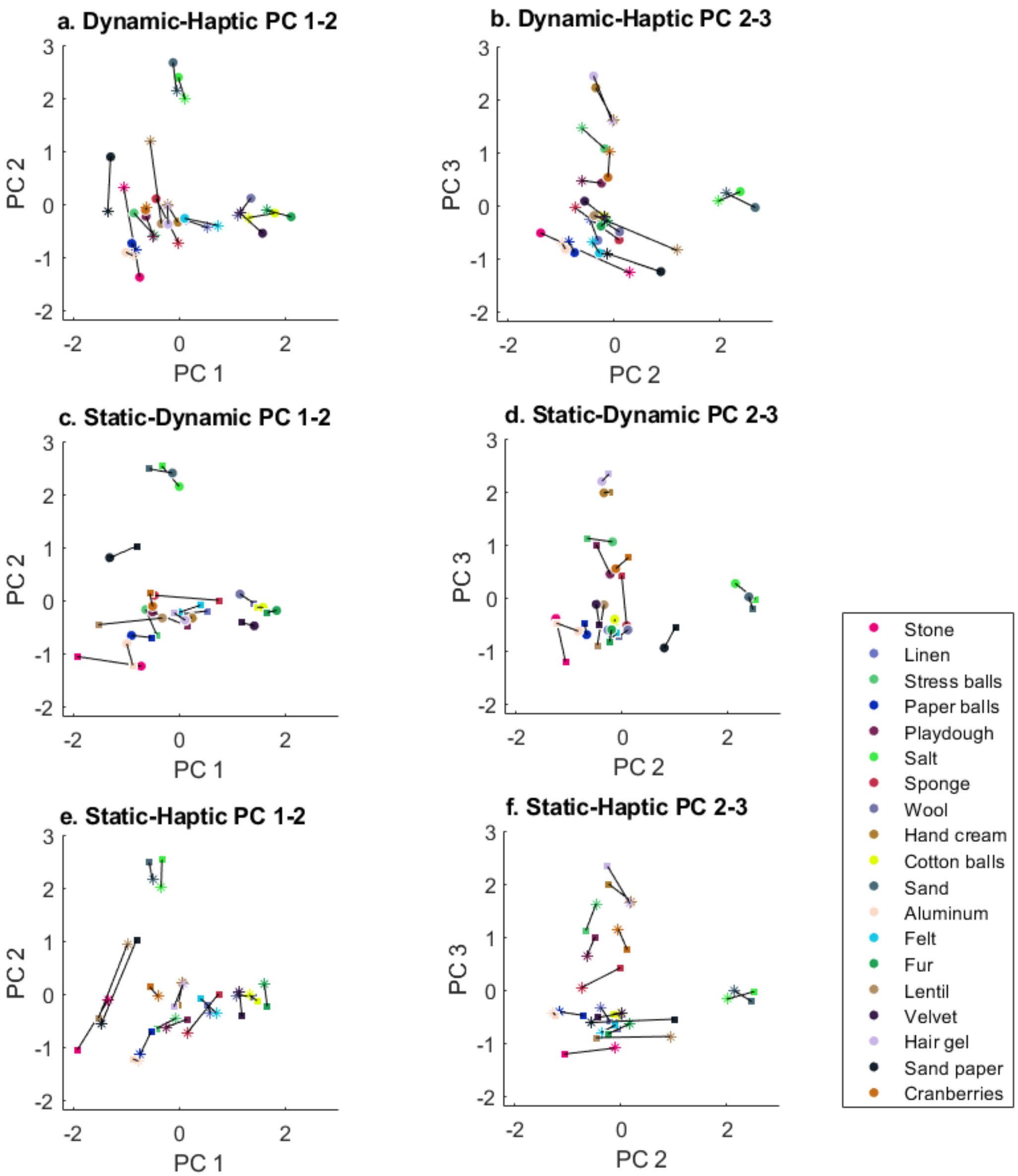
5. Pressure: "Applying directional normal force to squeeze a material between palm and fingers or using one or more fingers to apply normal force."



Supplementary Figure 1. **Consistency across participants.** Correlation coefficients across participants for (a) static (b) dynamic (c) haptic conditions (Pearson's correlation for each pair of participants across 19 materials times 15 adjective ratings). High correlations are plotted in dark blue and low correlations are plotted in light blue (white would be $r = 0$). Correlations of Ratings across participants were ranging between .45 to .86, .41 to .81, and .41 to .95, sequentially for haptic, static visual information, and dynamic visual information conditions and all were statistically significant at $p < .01$.



Supplementary Figure 2. Mean inter-observer consistency per adjective. Mean correlation coefficient across materials and participants per adjective in static, dynamic, and haptic conditions. Mean correlations range from.45 to .82, .47 to.84, and .40 to .86, in static, dynamic and haptic conditions, respectively.



Supplementary Figure 3. Procrustes analysis of the change in Bartlett score values of each material across the three perceptual softness dimensions: surface softness, granularity, viscosity when mapping from dynamic to haptic (a. dynamic-haptic principal component 1 vs 2, b. dynamic-haptic principal component 2 vs 3), static to dynamic (c. static-dynamic principal component 1 vs 2, d. static-dynamic principal component 2 vs 3), and static to haptic (e. static-haptic principal component 1 vs 2, f. static-haptic principal component 2 vs 3). Each symbol represents one condition (dot: dynamic, square: static, and star: haptic). The second title condition indicates the transformed spaces.

List of Publications

Journal Articles

Cavdan, M., Doerschner, K., & Drewing, K. (accepted for publication). Task and material properties interactively affect softness explorations along different dimensions. *IEEE Transactions on Haptics.* doi: 10.1109/TOH.2021.3069626.

Cavdan, M., Drewing, K., & Doerschner, K. Materials in action: The look and feel of soft

(under review). *Journal of Vision.*

Güngör, D., Yildiz, G. Y., & **Cavdan, M.** (under review). Biculturalism Benefits Creativity when Personal Values Match Cultural Norms. *Psychological Studies*.

Cavdan, M., Cheeseman, J., Pisu, V., Mehraeen, S., Ernst, M. O., Adams, W. J. Effects of sphericity and linear extent on visual and haptic volume perception (in preparation for submission).

Conference Articles

Cavdan, M., Doerschner, K. & Drewing, K. (2019). The many dimensions underlying perceived softness: How exploratory procedures are influenced by material and the perceptual task*. In *IEEE World Haptics Conference (WHC)*, Tokyo, Japan, 2019, pp. 437-442, doi: 10.1109/WHC.2019.8816088.

Cavdan, M., Freund, A., Trieschmann, A. K., Doerschner, K., Drewing, K. (2020). From Hate to Love: How Learning Can Change Affective Responses to Touched Materials. In: Nisky I., Hartcher-O'Brien J., Wiertlewski M., Smeets J. (eds) Haptics: Science, Technology, Applications. EuroHaptics 2020. Lecture Notes in Computer Science, vol 12272. Springer, Cham. https://doi.org/10.1007/978-3-030-58147-3_7

Cavdan, M., Ennis, R., Drewing, K., & Doerschner, K. (accepted for publication). Constraining haptic exploration with sensors and gloves hardly changes multidimensional structure of softness perception. *World Haptics Conference,* Canada (2021).

Conference Abstracts

Cavdan M., Özgen, E., Witzel, C. (accepted to V-VSS 2021). How to make a #TheShoe.

Cavdan, M., Drewing, K. & Doerschner, K. (2020). Materials in action: The look and feel of soft. *Journal of Vision* 2020;20(11):514. doi: https://doi.org/10.1167/jov.20.11.514.

Cavdan, M., Drewing, K., & Doerschner, K. (2019). Visual and haptic softness dimensions. European Conference on Visual Perception, Leuven, Belgium.

Declaration

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