Computation of sensory-affective relationships depending on material categories of pictorial stimuli

Shogo Okamoto, *Member, IEEE,* Kohta Wakamatsu, Shigeki Nakauchi, Jinhwan Kwon, Maki Sakamoto

Abstract—Exposure to stimuli gives rise to sensory and affective experiences. Computing the relationships between these experiences is instrumental to designing affectively appealing products and understanding human experiences. Hierarchical structures of sensory and affective responses, which can be built through adjective rating tasks, are regarded as an effective means for expressing relationships between sensory and affective responses. Naturally, these hierarchical structures depend on the type of stimulus; however, so far, their dependencies on material categories have yet to be examined. We therefore investigated how hierarchical structures of affective and sensory responses depend on seven material categories: fabric, leather, wood, paper, foliage, stone, and glass. Each material category had 100 visual representations selected from the Flickr Material Database. Thirty-nine participants were asked to rate 368 pictures across a set of materials. The questionnaire adjectives included visually- and haptically-centered items although the stimuli were purely visual. We found that the structures differed substantially among the material categories, although there were some commonalities. Particularly, the positions of polysemic or multimodal adjectives such as "light" and "uncomfortable" in the hierarchy were highly dependent on the material category. For example, "light" has both physical (lightweight) and psychological (e.g., non-solemn, cheerful) meanings. For stone and glass (generally considered to be of heavy weight), the psychological meanings were primarily considered. Conversely, the physical meanings were predominant for fabric, leather, wood, paper, and foliage, for which weight is a factor in judging quality. The present study helps interpret affective descriptors whose meanings vary among types of stimuli.

Index Terms—Structural equation modeling, Flickr material database, Layered structure, Material perception, Affective responses

1 Introduction

Humans experience changes in sensory and affective states when exposed to products or sensory stimuli. The affective responses, despite being linked to the perceived value of products, do not seem to be directly linked with the physical properties of stimuli. Therefore, it is challenging to estimate how they change along with the physical properties of products. Hence, numerous researchers have attempted to explain or predict affective responses by using sensory adjectives, which are directly associated with the physical properties of the stimuli. To this end, many studies have created hierarchical models wherein scores are given to sensory adjectives, which are then linked to scores of affective adjectives through unimodal or multimodal sensory appraisals [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15].

These studies used their own methods of hierarchical modeling. Most studies sought to establish two-layered models with sensory and affective adjectives at low and high layers, respectively [5], [7], [8], [11], [12]. The low and high layers are typically connected by multivariate regression analyses. Other studies used multi-layered models constructed using tasks other than the adjective rating task [3], [14], [15], or had experts in a given field (e.g., food or clothing industries) determine the structures of the layers [1], [9], [10]. For example, Ueda [15] determined the hierarchy of 114 adjectives used for evaluating sounds on the basis of their abstractness, complexity, objectiveness, and difficulty, judged by 116 experimental participants. In [1], a hierarchical model to represent the sensory and affective experiences while having coffee was made by means of agreement among baristas. Multi-layered models allow for connections among the affective variables and can express more complex relationships among the affective responses; hence, they represent affective responses more accurately. For example, in [13], the mean correlation coefficient between the observed and modeled ratings of five types of affective descriptors was 0.67 for a two-layered model whereas it was 0.75 in a four-layered model.

Fig. 1 provides an example of the layered structure of such a model. The sensory adjective scores are laid in the bottom layer and are directly linked to (i.e., they psychophysically capture) the physical properties of stimuli. These sensory adjectives include "rough," "warm," etc. The affective adjectives are instead typically located in the middle and higher layers of the model and are explained by adjectives in successively lower layers. The higher-layer adjectives tend to pertain to hedonic or evaluative aspects,

- *S. Okamoto is with the Department of Mechanical Systems Engineering, Nagoya University, Japan.*
- *K. Wakamatsu and S. Nakauchi are with the Department of Computer Science and Engineering, Toyohashi University of Technology, Toyohashi, Japan.*
- *J. Kwon is with the Faculty of Education, Kyoto University of Education, Kyoto, Japan.*
- *M. Sakamoto is with Graduate School of Information Systems, The University of Electro-Communications, Chofu, Japan.*

Manuscript received June 11, 2019.

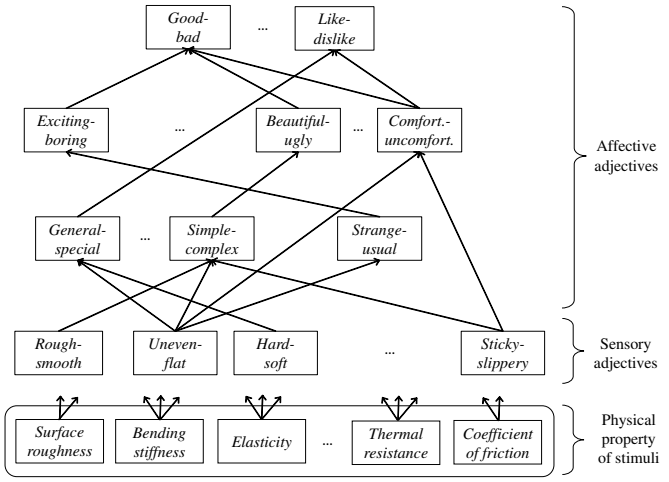


Fig. 1. Layered structure of sensory and affective adjectives. Sensory adjectives are directly linked with the physical properties of stimuli. The affective adjectives in the middle to high layers are explained by successively lower layers. Evaluative and hedonic aspects are generally placed in the higher layers. This figure is consistent with [6].

whereas the middle-layer adjectives tend to describe the attributes of stimuli [1], [2], [4], [9], [14]. These layered models provide semantic relationships between sensory and affective responses, which can help in designing the affective values of products and interpreting the meanings of conceptual values expressed by affective adjectives. Thus far, these models have been leveraged for various products including beverages [1], clothing [10], car seats [8], leather [9], and wood [12].

In the present study, we establish hierarchical structures of sensory and affective adjectives based on the scores assigned to these adjectives in a sensory appraisal task involving the presentation of pictures of seven material categories including fabric, paper, wood, leather, foliage, glass, and stone. We then discuss the similarities and differences in the sensory-affective relationships between these materials using the hierarchical models of adjectives. As described in the following two paragraphs, thus far, such sensory-affective relationships have not been compared among material categories.

Thus far, using visual and haptic cues, sensory responses to material surfaces and material classification have been extensively studied [16], [17], [18], [19], [20], [21]. These studies showed that sensory responses depend on material categories. For example, using computer graphics of several material categories, Hiramatsu et al. [16] found that the images of similar material categories formed clusters in the perceptual space. Baumgartner et al. had similar results using either visual or haptic material perception [19] where the perceptual spaces made by the two sensory cues were close to each other. However, these studies did not focus on the associations between perceptual and affective qualities.

In contrast, earlier studies on sensory and affective qualities did not focus on the differences between material categories. For example, Drewing et al. investigated the relationships between the affective qualities and dimensions of perceptual qualities using 47 types of objects to be touched [5]. However, they did not analyze their results from the viewpoint of material categories, and the model was applied to a set of differing materials. Fujisaki et al. [12] compared the relationships between sensory and affective responses to natural woods according to the sensory cues available (i.e., when only tactile, visual, or auditory cues were available); they found that the relationships were similar across all three modalities. They also found different sensory-affective relationships between responses to wood and stone. However, to our knowledge, the sensory-affective relationships have not been compared among several types of material categories. Furthermore, it remains unclear how responses to affective adjectives that are polysemic and indefinite depend on the material category. Understanding how these relationships differ by material category could provide a more concrete scientific basis with regard to the industrial design of products.

The potential contribution of the present study to industrial fields is as follows: In manufacturing, the affective aspects experienced from materials are valued [22], and, thus far, systematic material-selection methods have been studied [23], [24], [25]. For example, Karana et al. proposed a method to help product designers to select materials such that the affective attributes of products and materials matched [23]. For customer–vendor communication about products, customers tend to use indefinite affective words to convey their demands. In these situations, the designers need to comprehend the meanings of affective descriptions. The present study provides a computational approach for such purposes. Further, for designers of publication and web pages, in addition to their own professional knowledge and feelings, they may refer to the hierarchical models established in this study as an aid with which to select pictures that suit the contents of their texts. For example, the results of the present study suggest that the impression of comfort for stone is more psychological, and those appearing more beautiful are felt to be more comfortable, whereas for other material categories, comfort is mostly determined by the predicted mechanical comfort in touch. Although the present study does not address image features, if they are incorporated into our hierarchical models, the sensory and affective impressions of pictures, which are not used for training in the models, may be estimated. For example, low-level image features can be linked with personal traits of picture preferences [26] and perceptual qualities of object surfaces [16].

2 Materials and Methods

The study was approved by the institutional review board of Toyohashi University of Technology.

2.1 Materials: Pictures of seven material categories

To investigate the relationships among sensory and affective responses, one approach is to use a stimulus set, where image features pertaining to one type of sensory quality is manipulated while controlling for the other parameters. However, there are no general methods to manipulate parameters corresponding to specific perceptual qualities for natural images. Therefore, we used material pictures provided by the Flickr Material Database (FMD) [27], for

Fig. 2. Exemplar pictures of the seven materials categories. Those actually used in the experiments are not shown because of copyright concerns, but they can be seen on the Flickr Material Database [27] website.

which multiple perceptual and affective properties vary simultaneously among pictures. Because of the accessibility of the database, we used image stimuli; nonetheless if the task is extended to other cues, i.e., haptic sensations, then a certain level of consistency can be expected between the results from visual and haptic tasks, although they may not fully agree with each other [18], [28]. Especially, perceived weight [29] may substantially differ among the visual and haptic cues.

We used only colored pictures because color is part of the properties of natural and artificial materials, whereas monochrome and colored pictures were compared in some studies [20], [30]. We selected pictures that focused merely on the materials and that give no indication of the object. For example, some pictures were of glass cups, leather bags, wooden eating utensils, etc.; we excluded these object pictures. To retain a sufficient number of pictures (i.e., one hundred for each material category), we selected seven material categories: fabric, leather, foliage, glass, stone, paper, and wood[1]. The stone category did not include gems. These categories are typically used in the studies of visual material perception [16], [17], [18], [20], [21].

The material categories of the FMD pictures analyzed in the present study were easily identified with a success rate of 89% in our follow-up test, which involved seven participants, different from those who participated in the main task[2]. This value is similar to the rate reported in [30] where 91% of close-up and object images were correctly classified.

As shown in supplementary materials (Figs. A–C), the randomness of these pictures is suggested by the histograms of participants' subjective answers of perceptual and affective qualities to pictures. Their distributions are not fully random, but the answers moderately gathered within limited ranges, with some pictures outlaid from the majority. These suggest that pictures causing a variety of sensory and affective qualities are included in each material category.

1. To establish a database, we also used pictures of water, plastic, and metal. However, in the present study, we excluded these pictures from the analysis because the majority of pictures of metal and plastic materials contained objects or products such as eating utensils, machine tools, and coins for metal products, and did not focus on the surfaces. Pictures of water are largely snapshots taken during motions such as flowing, falling, and dripping water. To reflect their affective properties, we needed a set of adjectives different from those for other material categories.

2. We excluded object images; however, the material classification rate was high. This is mainly because the tested images did not include plastic materials which are generally confusing.

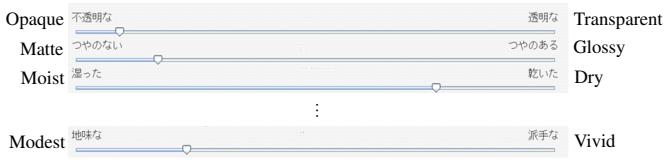


Fig. 3. Visual analog scales for the questionnaire

Fig. 2 provides exemplar pictures of each material. The pictures were presented using a 32-inch LCD monitor with 1920 × 1080 pixels in a dark room.

2.2 Participants

Thirty-nine university students (30 men and 9 women, 20–25 years old with the mean ± SD: 22.1 ± 1.2, native Japanese speakers) who responded to an open advertisement participated in this study after providing their written informed consent. They majored in engineering and were paid as determined by the institutional review board: 900 JPY/h. They reported normal or corrected-to-normal visual acuity. They had normal color vision as tested with Ishihara 38 color plates.

2.3 Procedures: Rating tasks of pictures

The participants rated each picture on a computer screen using numerous visual analog scales, as shown in Fig. 3. The extremities of these scales consisted of the two adjectives of each dyad, while the center of the scale, at which the sliders were initially positioned, was neutral. The adjectives included *rough–smooth*, *hard–soft*, *cold–warm*, *sticky–slippery*, *moist–dry*, *matte–glossy*, *opaque–transparent*, *uncomfortable–comfortable*, *modest* (*plain*)*–vivid* (*loud, bold*), *light–heavy*, *ugly–beautiful*, *cheap–luxury*, and *restless–relaxed* (*calm*). All words were presented in participants' native language (i.e., Japanese)[3]. Although some of the adjectives are innately haptic, researchers have shown that visual images can also give rise to haptic properties , e.g., [31], [32], [33], [34], [35], [36], [37]. For example, looking at glossy and rough material images activates the somatosensory area associated with tactile stimulation [37]. In earlier studies on visual material perception or classification, haptic adjectives, such as hard, elastic, fragile, and cold, were also used [16], [17], [18], [20], [21] considering the cross-modal connections between visual and haptic sensations. The participants were not provided any definition of the adjectives.

The descriptors selected were based on related studies so that the number of descriptors would not be large. The first

3. The corresponding Japanese words for the above list of adjectives are as follows: *arai–nameraka*, *katai–yawarakai*, *tsumetai–atatakai*, *nebatsuku–suberu*, *simetta–kawaita*, *tsuyanonai–tsuyanoaru*, *futomeina–tomeina*, *fukai–kaiteki*, *jimina–hadena*, *karui–omoi*, *minikui–utsukushi*, *yasuppoi–kokyuna*, and *ochitsukinonai–ochitsukinoaru*, respectively. Furthermore, *artificial–natural* was rated aside the above thirteen adjective dyads; however, it was not analyzed in the present study.

seven adjective dyads are frequently used in the study of material perception by visual cues (e.g. [12], [17], [20]). The latter six dyads are used in the study of affective properties of materials (e.g. [7], [12], [14]). Nonetheless, the present study does not aim to exhaustively cover various types of affective properties. It aims to demonstrate how middle and higher levels of layered structures may differ among the different types of materials.

For the appraisal of affective states of humans, non-verbal methods such as [38], [39] are also available. However, both affective and sensory aspects are covered in the present study. Non-verbal approaches covering these two types of aspects do not exist, and we selected the method based on descriptors.

Each participant rated 368 randomly selected pictures and different image sets. They included nearly equal numbers of pictures for each material category. On average, six or seven participants rated one picture. They took a break between every session containing 46 pictures and completed their assignments over 2 to 3 days to prevent strain. Each session required approximately 30 min. In total the experiment took approximately 5 hours.

2.4 Data analysis: Computation of hierarchical causal structure of sensory and affective responses

We used the method in [13] to compute the hierarchical structure of affective and sensory adjective scores. This method is based on structural equation modeling (SEM) [40], [41], which is suitable for analyzing causality among multiple variables. As aforementioned in the introduction (second paragraph), the structure among the scores of affective adjectives can be hypothesized and estimated more accurately in these models, than in two-layered models. The hypothesized models are statistically validated, as will be discussed below. Another merit of the method in [13] for the present study is that a multi-layered structure is established solely based on an adjective rating task and mathematical computation whereas other methods make use of, or require, experts' knowledge or another task for determining the hierarchy of adjectives (see the second paragraph in the introduction). In general, multiple models can statistically explain one observed dataset; however, the method in [13] allows us to establish a concise model by sequentially improving on the simplistic two-layered model. That is, layers in the model with the lowest modeling accuracy are continually developed until the entire structure is statistically acceptable.

The multi-layered modeling method in [13] yields a structure where sensory adjectives are placed at the bottom to explain the affective and evaluational adjectives in the middle and higher layers as in Fig. 1.

The sensory responses were the following adjectives: *rough–smooth*, *hard–soft*, *cold–warm*, *matte–glossy*, *opaque–transparent*, *sticky–slippery*, and *moist–dry*. All the adjectives are directly related to the physical properties of the material surfaces and can be largely judged or estimated by their appearances. In terms of non-visual adjectives i.e. *hard-soft*, *sticky-slippery*, and *cold-warm*, according to [18], the ratings in two tasks with either only haptic cues or visual cues, were highly correlated, suggesting that these non-visual properties are haptic-related visual properties, and can be judged visually.

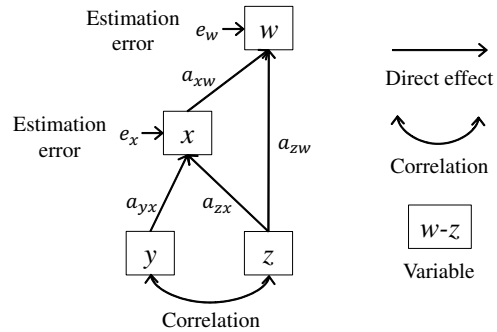


Fig. 4. Graphical expression of structural equation modeling. Unidirectional arcs and associated values are direct effects and their magnitudes, respectively. The effect values can be either positive or negative. Nodes are the observed variables after normalization. e is the model error, independent of the other variables and has a mean of zero.

The remaining six adjectives (*modest–vivid*, *cheap–luxury*, *restless–relaxed*, *ugly–beautiful*, *uncomfortable–comfortable*, and *light–heavy*) were placed on the higher layers of the model. *Light–heavy* is a haptic sensation, and visual judgment of this quality requires longer response times than does judgment of other visual qualities, such as glossiness and roughness [21]. Further, *light–heavy* tends not to be included in rating tasks of perceptual qualities for visual images of materials [17], [19], [20] because physical heaviness (i.e., weight) is not judged solely from images of surface material. Hence, *light–heavy* was not included in the sensory adjectives in the context of our visual task.

The layered structure created via SEM is graphically shown by using nodes and directed arcs in Fig. 4. The nodes present the continuous variables after normalization (in the present study, the z-scores of the adjective scores), while the directed arcs indicate a direct effect from one variable to another. The strength of influence a is either positive or negative. For example, the value of x is expressed as a linear summation of the effects of y, z, and model error e_x ($x = a_{yx}y + a_{zx}z + e_x$). The error follows a random distribution and has a mean of zero. The influence values a correspond to partial regression coefficients of the multivariate regression analysis. x is also used to explain a variable in the higher layer (i.e., w). Bidirectional arcs indicate that two connected variables (in the figure, y and z) are significantly correlated.

SEM determines the coefficients and statistical significance of the arcs in a layered structure, such that the observed and estimated covariance matrices of the variables resemble each other. To judge how accurately the hypothesized structure approximates the observed data, multiple indices of model fit are used [42], [43]. We used representative indices of the similarity between the observed and estimated covariance matrices, including the goodness-of-fit index (GFI), comparative fit index (CFI), and χ^2. The GFI and CFI range from 0 to 1; for statistically valid modeling, they should be greater than 0.90–0.95 [44], with the maximum value of 1 indicating a complete match between the two matrices. The χ^2 value should, on the other hand, be

non-significant and small (i.e., the p value should be greater than 0.05), indicating that the two covariance matrices are not statistically different.

As well as the statistical validity, the semantic validity of the established model is also important for SEM, which will be discussed in Secs. 4.1 and 4.2. The meanings of the models are evaluated on the basis of common sense and the literature available.

For each material category, we processed the adjective scores as follows. First, we transformed the visual analogue scores for individual participants for each adjective into z-scores for each material category such that their mean and standard deviation are 0 and 1, respectively. The value for each adjective dyad was bipolar: for example, if the value for *rough–smooth* was negative, it meant that the participant had rated the material picture as smoother than average in the material category. The z-scores were then averaged among the participants for each picture. We did not conduct any outlier tests for this calculation. The covariance matrix of the thirteen adjective dyads was then computed and used in the SEM. Sensory variables in the lower layer of the model were allowed to correlate with each other due to the specifications put in place. To conduct the SEM, we used the *sem* (version 3.1) package for *R*.

3 Results

For all material categories, the layered structures were successfully computed with p values greater than 0.05, and the GFI and CFI values were mostly greater than 0.95. Fig. 5 shows the layered structure of each material. All the unidirectional arcs are statistically significant ($p < .05$). For visual clarity, we do not show the correlations among the lower-layer sensory adjectives. Instead, they are summarized in Tables 1–7 in the Appendix. The adjectives that are not linked with the others are also not displayed. Further, we have omitted the graphical description of the errors. Instead, we note the R^2 value to indicate how accurately the value is estimated. R^2 represents the square value of the correlation coefficient between the observed and estimated values. For the same reason, each node displays only the adjective with the positive value.

The materials showed several common features. First, the higher layers tended to include *restless*, *modest*, and *cheap*, while the middle layer contained *light*, *ugly*, and *uncomfortable*. For the majority of materials, *hard*, *matte*, and *rough* influenced *light*, *modest*, and *ugly*, respectively. Despite these commonalities, the layered structures mostly differed according to the material category. For some materials, *cold*, *opaque*, and *moist* had no significant impact on higher-layer adjectives. For glass and stone, *light* was allocated to the higher part of the structure, although it was just above the bottom perceptual layers for the other materials.

To investigate the similarities in participants' responses among the materials, we calculated the distances between each of two material categories by using the following formula:

$$d_{ab} = \mathrm{tr}[(\boldsymbol{X}_{\mathrm{a}} - \boldsymbol{X}_{\mathrm{b}})^{\mathrm{T}}(\boldsymbol{X}_{\mathrm{a}} - \boldsymbol{X}_{\mathrm{b}})] \tag{1}$$

where $\boldsymbol{X}_{\mathrm{a,b}}$ are the covariance matrices for materials a and b, which were in separate material categories (i.e., one of paper, fabric, wood, leather, stone, glass, and foliage). This distance corresponds to the dissimilarity between two covariance matrices that define the structure among the observed variables (adjectives). With a greater distance value between two material categories, their variable structures are more different from each other. These distances were then used to compute the multidimensional scales of the covariance matrices [45], [46]. The covariance matrices of the seven material categories were arranged on a one-dimensional scale, with the stress value being 0.015. Their locations are shown in Fig. 6. Five material categories were closely placed, whereas glass and stone were at the two extremities. These patterns indicated that participants' responses were distinct for glass and stone, whereas they were similar for the other five types of materials.

Further, to investigate how sensory and affective responses varied among the material categories and pictures, we conducted a principal component analysis of the responses to pictures of all material categories for each set of the sensory and affective adjectives. As shown in Fig. 7 (a), the sensory responses to glass were substantially different from those of the other materials. In contrast, the responses to paper, fabric, and leather exhibited some similarities that is, they were closely located. The responses to stone tended to be dissimilar to those of the others, but slightly similar to the responses to wood. As shown in Fig. 7 (b), these trends were true for the affective responses as well. Thus, the sensory and affective responses depended on the material categories, although they naturally varied within each category because of the variety of pictures.

4 Discussion

4.1 Commonalities of fabric, leather, paper, wood, and foliage

The shared link for all types of materials was that between *hard* and *light*, with the other connections differing among the materials. Still, as shown in Fig. 6, we found similar questionnaire results for fabric, leather, foliage, wood, and paper, and their layered structures were also rather similar. Note that these five types of material categories were grouped into one, such that the following discussion is easy, and we do not conclude that they have the same variable structures. Fig. 8 shows a structure computed based on the questionnaire responses from these five material categories. This can be constructed as a common structure for these material categories, and we discuss its characteristics and semantic validity below.

Light and *hard* were strongly connected in a negative manner. *Light* corresponded with weight, and the softer the surfaces in the pictures appeared, the lighter the pictures were scored. This is physically reasonable because soft objects tend to be of low density and are expected to be light in weight, which agrees with [12], [21]. They are, however, judged to be independent, depending on experimental contexts [5].

Ugly was moderately connected with *rough* and *cold*. Rougher surfaces were tended to be judged as uglier, as were pictures with high *cold* scores; this suggests that *ugly* refers not only to the apparent beauty of an object but also haptic aspects. Impressions of beauty and thermal cues

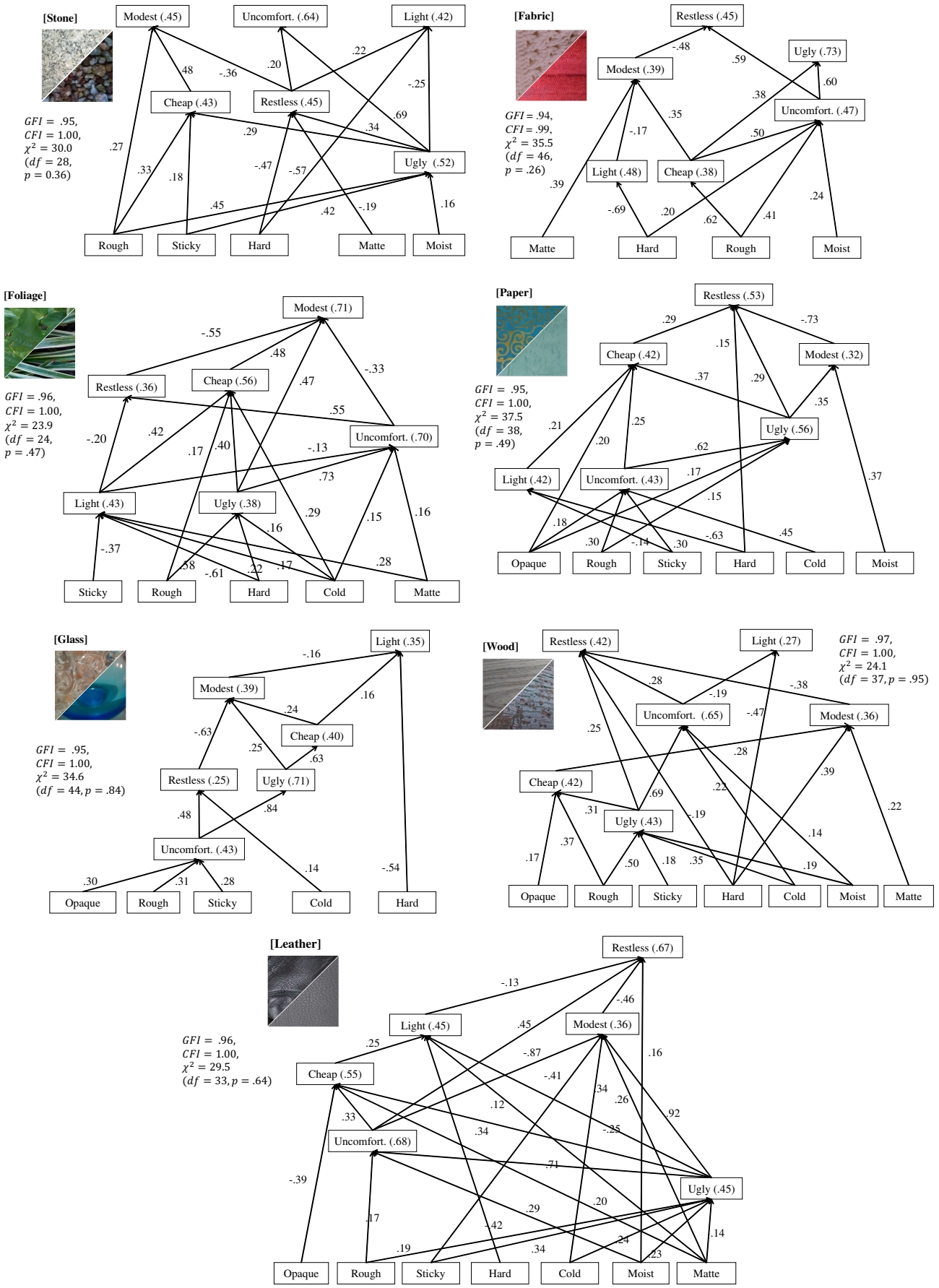


Fig. 5. Layered structure of affective and sensory responses to each of the seven types of materials. The adjectives that are not linked with any others are not shown. Values associated with the links are the strength of influences. Values in parentheses are R^2 values. df means the degree of freedom of the model.

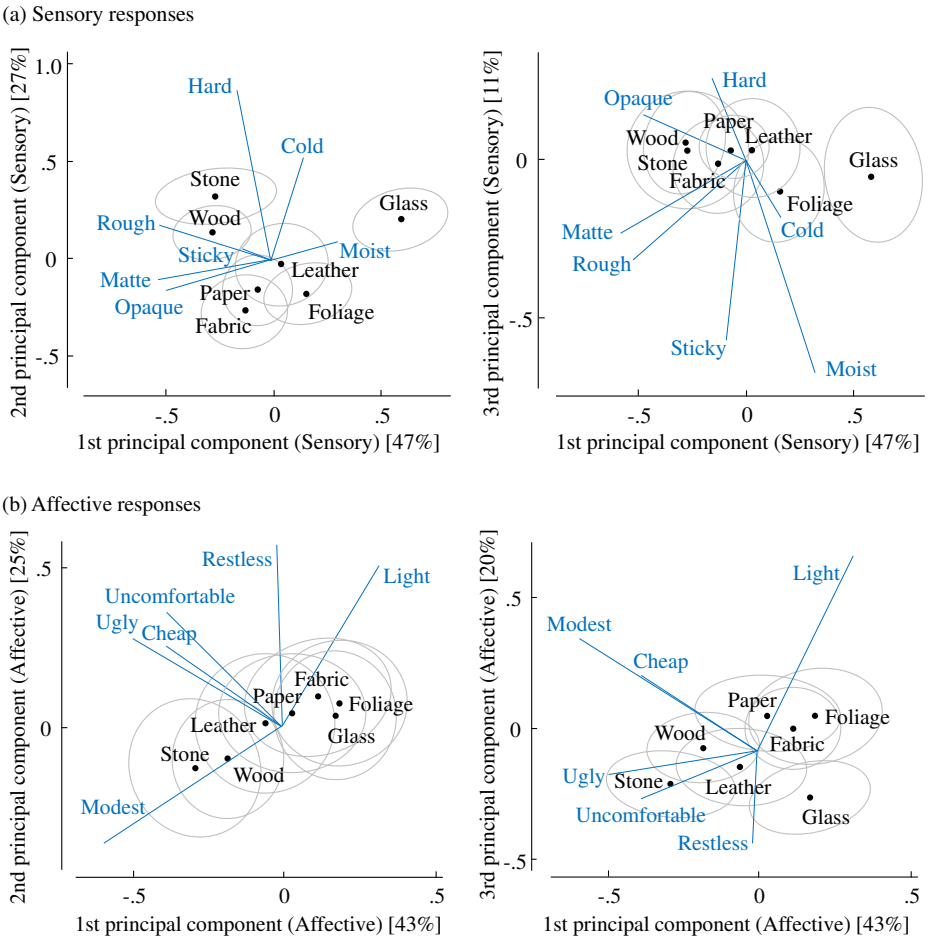


Fig. 7. Materials plotted on the reduced principal-component space. Dots and ellipsoids are the centroids and standard deviations among the pictures, respectively. The values in brackets are the contribution ratios of the principal components.

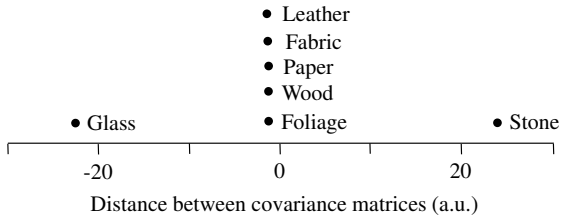


Fig. 6. Loci of the material categories on a distance scale of their covariance matrices.

are known to be synesthetic in the haptic perception of materials [47] whereas it is not clear whether this finding fits into the present visual task. Furthermore, a study on visual impression of furniture reported the relationships among *ugly*, *rough*, *modest*, and *uncomfortable* [48], which is comparable with the relationships in Fig. 8.

Uncomfortable was influenced by *sticky*, *cold*, and *ugly*, which in turn were influenced by *rough*, *cold*, and *matte*. These connections suggest that *uncomfortable* largely corresponded to the mechanical unpleasantness of touch [12], [49], [50], [51], [52], [53], [54], and that pictures that appeared to stimulate the skin were judged as unpleasant.

Cheap was directly explained by *ugly*, *uncomfortable*, *modest*, *light*, and *rough*, which are reasonable features for low-price surfaces. For example, woods that appeared light and modest were judged to be cheap [12].

Restless is a complex characteristic comprising visual beauty (*ugly*) and mechanical comfort (*uncomfortable*), which means that relaxed (i.e., relieved) experiences are achieved by visually beautiful and mechanically comfortable stimuli. Even when using visual or tactile cues only, feelings of relief (or relaxation) and comfort are strongly correlated [5], [12], [47].

We speculate that *modest* is conceptually similar to *relieved* (the opposite of *restless*) because of their strong association. In other words, modest pictures tend to be perceived as relieving as well. *Modest* is directly linked with *matte* and *hard* and indirectly with *opaque* by way of *ugly*, which is consistent with [55].

All these connections are reasonable and indicate that the affective and evaluative relationships of the pictorial stimuli were reasonably captured.

4.2 Distinctive characteristics of stone and glass

As shown in Fig. 6, the covariance matrices of stone and glass were substantially different from those of the other materials used in our study. Thus far, several studies have

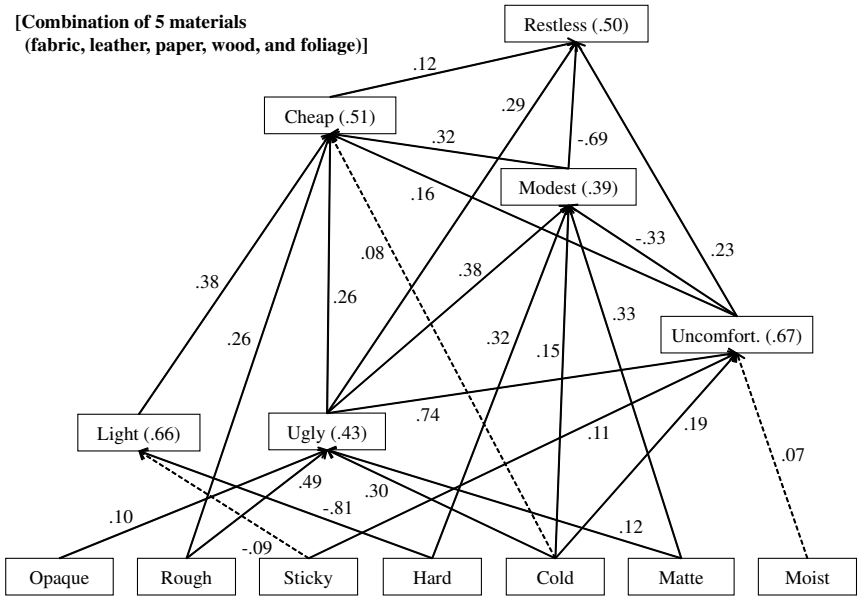


Fig. 8. Layered structures computed for responses to fabric, leather, paper, wood, and foliage. $GFI = .99$, $CFI = 1.00$, and $\chi^2 = 27.3$ ($df = 33$, $p = .74$). Dotted lines are weak but significant connections.

analyzed the similarities in the subjective ratings of the perceptual features of images belonging to a variety of material categories. These studies differed in the material categories, questionnaires, panelist backgrounds, and analyses used; hence, the conclusions are inconsistent. For example, in some studies, wood and stone exhibited similar responses in questionnaires [17], [18] whereas in the other studies, the responses for these categories were very different [12], [16], [20], [21]. The studies seem to weakly agree that the responses to leather and fabric are similar. However, the majority of these studies exhibited dissimilarities between stone and glass [16], [17], [20], [21][4], which agrees with our similarity analysis among the material categories, as in Figs. 6 and 7.

In the structure for stone, unlike the other materials, *light* and *uncomfortable* were placed in the higher layers. *Light* was directly influenced by *hard*, *ugly*, and *restless*. This suggests that *light* carried the psychological meanings ("gentle," "delicate," "cheerful," "non-solemn," and "non-serious") as well as the physical one (i.e., "lightweight") [56]. Visual ugliness might have imbued a picture with non-delicate and non-gentle (heavy) impressions, whereas restless pictures may have seemed cheerful (light). For the other materials, we speculate that *light* largely meant "lightweight" because *light* was almost solely influenced by *hard* as in Fig. 8. In contrast, stones are usually heavy and less distinctive in terms of their weight. Hence, the psychological meanings might have become more salient for stone.

For the majority of material categories, pictures that looked smooth, soft, and warm were rated as comfortable. As noted above, *uncomfortable* seemed to be felt as the—strength of mechanical stimuli on the skin or body—that is, mechanical unpleasantness. However, for stone, *ugly* and *restless* stimuli were strongly related with *uncomfortable*, suggesting that *uncomfortable* also reflects visual unpleasantness. Visual aesthetic value might have been more influential for the impression of comfort when compared to physical pleasantness because most stone objects are haptically uncomfortable due to their surface roughness, hardness, and coldness.

The adjective structure for glass also differed from those of the majority of other materials. Similar to the structure of stone, *light* was placed in the highest position. *Light* was linked with *hard*, *cheap*, and *modest*, suggesting that it carried both physical and psychological meanings. The direct negative effect of *modest* on *light* suggests that modest glasses were felt as serious and solemn, which are the opposite meanings of *light* in the psychological sense. Furthermore, the direct effect of *cheap* on *light* suggests that cheap glasses were felt as non-serious (i.e., *light*). The effect of *cheap* to *light* was also rather complicated. *Cheap* had a direct positive influence on *light*, but also an indirect negative influence via *modest*. The affective responses in the higher layers of the structure appear to be underlaid by complicated causality. It also bears noting that the R^2 value of *light* was merely .35, indicating that further adjectives are necessary to fully describe this polysemic concept. For example, adjectives related to artistic values of glass might be helpful for explaining the responses to *light*.

Light in the structure for wood appears exceptional. *Light* was placed in the highest layer for wood, unlike for fabric, paper, leather, and foliage, although these five types of materials exhibited similar covariance matrices of adjective scores. For wood, *light* might be an irregular case because its R^2 value was the smallest of all material categories. In other words, the scores for *light* could not be well explained by the other adjectives. For the quality judgment of wood, attributes such as sturdiness, newness, and cleanliness are substantial factors [12]; however, these adjectives were not used in the present study. Both the appearance and impression of wood changes substantially with its age. For example, new wood looks clean and the surface of old wood

4. Glass was not used in [18].

does not look sturdy. These attributes might be related with impressions of *delicate* and *solemn*, which are both included in the meanings of *heavy* i.e. the opposite of *light*. Age might be an important factor for evaluating wood; however, this attribute was not included in our study, which might have resulted in the low R^2 values for *light*.

4.3 Dependence of layered structures on materials

Our main focus in this study was whether the semantic structures of sensory and affective responses were different or similar among the different material categories. The results in section 4.1 indicated that fabric, leather, paper, wood, and foliage exhibited similar structures, while the findings in section 4.2 suggest that glass and stone exhibited different structures.

The polysemic nature of affective adjectives might be responsible for the variations in the structures of affective responses. Some affective adjectives have both physical and psychological meanings and the salience of these meanings might depend on the material categories.

For example, as mentioned in section 4.2, for typically heavy materials such as stone, participants seemed to have focused on the psychological meanings of the adjective pair *light–heavy* as well as the physical meanings.

For fabric, paper, leather, wood, and foliage, *uncomfortable* corresponded to the mechanical unpleasantness. In contrast, for stone, *uncomfortable* was affected by *restless* and *ugly*, indicating that the visual unpleasantness was more activated. We might attribute this finding to the fact that the tactile comfort of stones is not usually discussed because stone is generally uncomfortable due to its harsh and hard surface. As such, for stone, comfort seemed to be based primarily on its visual properties rather than its visually estimated, tactile properties.

Taken together, the results above suggest that the salience of the meanings of polysemic adjectives vary with the material category involved, which in turn, explains the differences in the hierarchical structures of adjectives. This resembles the phenomenon where the meanings of polysemic words are automatically selected in specific contexts while reading [57], [58], [59]. Lexical processing is activated through pictures [60], [61], and thus the pictorial stimuli used in the present study might have influenced the comprehension of polysemic affective adjectives.

In terms of the sensory adjectives, some distinctions were also observed among the different material categories. *Cold*, *moist*, or *opaque* were not significantly linked with the other adjectives for some material categories, probably because they do not represent the characteristics of these materials. For example, most glass materials are glossy, meaning that *moist* and *matte* are not appropriate words to express their differences.

4.4 Limitations of the study and future issues

Some pictorial characteristics that we did not consider in the experiment could have weakened the accuracy of the model. The material pictures comprised shapes, colors, and surface patterns, in addition to their material characteristics. Shape has been shown to influence abstract or affective impressions [62], [63], [64], [65], [66], [67], while the color of the pictures is known to influence judgments of warmth [34], [35], [36], [68], roughness, and softness [34], [69]. Colors are also linked with some affective features [17], [20], [70]. The removal of color (usage of gray images) may be an effective method for excluding the effects of color, especially when gray images do not deter material classification ratio [30]. These features, including shapes, surface patterns, and colors, are intrinsic properties of materials and we consider that they should not be fully controlled for.

As mentioned in Sec. 2.1, we did not use metal and plastic materials because many pictures in FMD are not close-up pictures. Also, FMD does not include ceramic and rubber, which are sometimes used in the study of material perception [16], [20]. In future, these materials will be tested with new pictures to complete our study.

Similarly, if we use different adjective words in the rating tasks, the similarities among the seven types of material categories may change. For example, we did not include *natural-artificial* or *live-dead*, for which foliage may evoke unique response. Further, as aforementioned in Sec. 4.2, *new-old* seems an important property for the perception of wood. Hence, we should note that the similarities of the sensory-affective relationships appear different, depending on the descriptive word sets used, in the rating tasks.

The layered structures computed in the present study indicate the semantic relationships of adjective ratings, and therefore are different from the actual neural systems involved. Information processing in the human affective and hedonic systems is flexible, and thus may differ depending on material category. The SEM method is a linear approximation, whereas human perceptual and affective linkages are likely to be nonlinear [71]. Additionally, SEM does not account for recurrent structures. Hence, SEM might not perfectly express the actual neural processing of the relationship between sensory and affective responses. In addition, SEM does not provide a definite conclusion on the relationships of observed variables; the structures tested in this study by using SEM are but some of the statistically possible structures.

In the present study, still pictures were tested mainly because of the availability of FMD images. Previous studies have indicated that moving and interactive images enhance sensory properties such as the softness and glossiness of materials [72], [73]. Hence, in the future, our approach will be coupled with videos focusing on materials. Further, the perceptual dimensions of visual and haptic material perception are similar to each other, except for the properties unique to visual perception such as colorfulness and glossiness [12], [18], [74], [75]. However, in terms of the affective responses, the similarity between the visual and haptic cues has yet to be established. Hence, the findings in the present study are limited to pictorial stimuli.

5 Conclusion

In the present study, we had participants rate pictures of seven material categories using seven sensory and six affective adjectives. Through SEM, we created a layered structure that semantically and statistically explained the observed adjective scores for each material category. Participants' responses for five material categories—fabric, paper, wood,

leather, and foliage—were similar. For these materials, the responses to *relieved–restless*, *vivid–modest*, and *luxury–cheap* were in the higher layer of the structure and were influenced by the other affective and sensory responses. In contrast, for stone, *light–heavy* and *comfortable–uncomfortable* appeared in the high layers, while for glass, *light–heavy* occupied the highest position in the structure. We speculate that the relative importance of the physical (weight) and psychological meanings of *light–heavy* rely on the material category. For some materials, *light* is more physical, while for other materials, it is more psychological. Stone and glass are both heavy in weight, which perhaps makes the physical meaning of *light* less important or salient when evaluating their quality. Further, *comfortable* comprises a predicted mechanical pleasantness and visual beauty, and the precise meaning that arose may have depended on the materials involved. For stone, which is generally rough and unpleasant on the skin, *comfortable* might have been interpreted mainly as an aspect of visual beauty. The material-dependency of affective responses found through our adjective-rating tasks suggests the mutability of the human affective system.

CORRELATION COEFFICIENTS AMONG SENSORY RESPONSES

TABLE 1
Correlation coefficients among sensory variables for fabric. Significant values ($p < .05$)) are listed.

	Rough	Hard	Cold	Sticky	Moist	Matte
Hard	.15	-				
Cold	-.23	.45	-			
Sticky	.45	.19		-		
Moist	-.23	.40	.42	.20	-	
Matte	.63	-.21	-.45	.33	-.39	-
Opaque	.23	-.19	-.42		-.49	.35

TABLE 2
Correlation coefficients among sensory variables for paper. Significant values ($p < .05$)) are listed.

	Rough	Hard	Cold	Sticky	Moist	Matte
Hard	.19	-				
Cold		.37	-			
Sticky	.58		-.24	-		
Moist				.23	-	
Matte	.33		-.24		-.33	-
Opaque	.17				-.40	.52

TABLE 3
Correlation coefficients among sensory variables for leather. Significant values ($p < .05$)) are listed.

	Rough	Hard	Cold	Sticky	Moist	Matte
Hard	.30	-				
Cold	.23	.58	-			
Sticky	.40	.17		-		
Moist	-.24				-	
Matte	.49		-.17	.34	-.23	-
Opaque		-.18	-.19		-.26	.30

TABLE 4
Correlation coefficients among sensory variables for stone. Significant values ($p < .05$)) are listed.

	Rough	Hard	Cold	Sticky	Moist	Matte
Hard		-				
Cold			-			
Sticky	.41	-.52		-		
Moist	-.38	-.62		.22	-	
Matte						-
Opaque						

TABLE 5
Correlation coefficients among sensory variables for glass. Significant values ($p < .05$)) are listed.

	Rough	Hard	Cold	Sticky	Moist	Matte
Hard		-				
Cold			-			
Sticky	.44	-.47		-		
Moist		-.60		.44	-	
Matte	.64	-.28		.45		-
Opaque	.36			.18	-.23	.52

ACKNOWLEDGMENTS

This study was partly supported by JSPS Kakenhi (15H05922 and 15H05923) and (17K20002).

REFERENCES

[1] T. Nishino, M. Nagamachi, and M. Sakawa, "Acquisition of kansei decision rules of coffee flavor using rough set method," *Kansei Engineering International*, vol. 5, no. 4, pp. 41–50, 2006.

[2] X. Chen, C. J. Barnes, T. H. C. Childs, B. Henson, and F. Shao, "Materials' tactile testing and characterization for consumer products' affective packaging design," *Materials and Design*, vol. 30, pp. 4299–4310, 2009.

[3] S. Okamoto, H. Nagano, K. Kidoma, and Y. Yamada, "Specification of individuality in causal relationships among texture-related attributes, emotions, and preferences," *International Journal of Affective Engineering*, vol. 15, no. 1, pp. 11–19, 2016.

[4] K. Kidoma, S. Okamoto, H. Nagano, and Y. Yamada, "Graphical modeling method of texture-related affective and perceptual responses," *International Journal of Affective Engineering*, vol. 16, no. 1, pp. 27–36, 2017.

[5] K. Drewing, C. Weyel, H. Celebi, and D. Kaya, "Systematic relations between affective and sensory material dimensions in touch," *IEEE Transactions on Haptics*, pp. 1–1, 2018.

[6] H. Nagano, S. Okamoto, and Y. Yamada, "Modeling semantically multilayered affective and psychophysical responses toward tactile textures," *IEEE Transactions on Haptics*, vol. 11, no. 4, pp. 568–578, 2018.

[7] S. Guest, J. M. Dessirier, A. Mehrabyan, F. McGlone, G. Essick, G. Gescheider, A. Fontana, R. Xiong, R. Ackerley, and K. Blot, "The development and validation of sensory and emotional scales of touch perception," *Attention, Perception & Psychophysics*, vol. 73, pp. 531–550, 2011.

[8] T. Matsuoka, H. Kanai, H. Tsuji, T. Shinya, and T. Nishimatsu, "Predicting texture image of covering fabric for car seat by physical properties," *Journal of Textile Engineering*, vol. 54, no. 3, pp. 63–74, 2008.

[9] I. H. M. Hashim, S. Kumamoto, K. Takemura, T. Maeno, S. Okuda, and Y. Mori, "Tactile evaluation feedback system for multi-layered structure inspired by human tactile perception mechanism," *Sensors*, vol. 17, p. 2601, 2017.

[10] S. Kawabata and M. Niwa, "Objective measurement of fabric hand," in *Modern Textile Characterization Methods*, M. Raheel, Ed. CRC Press, 1996, pp. 329–354.

[11] R. Ackerley, K. Saar, F. McGlone, and H. B. Wasling, "Quantifying the sensory and emotional perception of touch: Differences between glabrous and hairy skin," *Frontiers in Behavioral Neuroscience*, vol. 8, no. 34, 2014.

[12] W. Fujisaki, M. Tokita, and K. Kariya, "Perception of the material properties of wood based on vision, audition, and touch," *Vision Research*, vol. 109, pp. 185–200, 2015.

[13] S. Okamoto, H. Kojima, A. Yamagishi, K. Kato, and A. Tamada, "Layered-modeling of affective and sensory experiences using structural equation modeling: Touch experiences of plastic sur-

TABLE 6
Correlation coefficients among sensory variables for foliage. Significant values ($p < .05$)) are listed.

	Rough	Hard	Cold	Sticky	Moist	Matte
Hard	-.16	-				
Cold		.35	-			
Sticky	.19	-.22		-		
Moist					-	
Matte	.64	-.22	-.17	.32		-
Opaque						

TABLE 7
Correlation coefficients among sensory variables for wood. Significant values ($p < .05$)) are listed.

	Rough	Hard	Cold	Sticky	Moist	Matte
Hard		-				
Cold		.22	-			
Sticky	.38	-.30		-		
Moist	-.34	-.37		.15	-	
Matte	.48			.22	-.24	-
Opaque	.24	.42			-.40	.30

faces as an example," *IEEE Transactions on Affective Computing*, 2018.

[14] H. Nagano, S. Okamoto, and Y. Yamada, "Semantically layered structure of tactile textures," in *Haptics: Neuroscience, Devices, Modeling, and Applications*, ser. Lecture Notes in Computer Science, M. Auvray and C. Duriez, Eds. Springer, 2014, vol. 8618, pp. 3–9.

[15] K. Ueda, "A hierarchical structure for adjectives describing timbre," *The Journal of the Acoustical Society of America*, vol. 100, no. 4, p. 2751, 1996.

[16] C. Hiramatsu, N. Goda, and H. Komatsu, "Transformation from image-based to perceptual representation of materials along the human ventral visual pathway," *Neuroimage*, vol. 57, pp. 482–494, 2011.

[17] R. W. Fleming, C. Wiebeland, and K. Gegenfurtner, "Perceptual qualities and material classes," *Journal of Vision*, vol. 13, no. 9, p. 9, 2013.

[18] E. Baumgartner, C. B. Wiebel, and K. R. Gegenfurtner, "Visual and haptic representations of material properties," *Multisensory Research*, vol. 26, pp. 429–455, 2013.

[19] ——, "A comparison of haptic material perception in blind and sighted individuals," *Vision Research*, vol. 115, pp. 238 – 245, 2015, perception of Material Properties (Part II).

[20] M. Tanaka and T. Horiuchi, "Investigating perceptual qualities of static surface appearance using real materials and displayed images," *Vision Research*, vol. 115, pp. 246 – 258, 2015.

[21] T. Nagai, T. Matsushima, K. Koida, Y. Tani, M. Kitazaki, and S. Nakauchi, "Temporal properties of material categorization and material rating: visual vs non-visual material features," *Vision Research*, vol. 115, pp. 259–270, 2015.

[22] E. Karana, P. Hekkert, and P. Kandachar, "Materials experience: descriptive categories in material appraisal," in *Proceedings of International Conference Tools and Methods in Competitive Engineering*, 2008, pp. 399–412.

[23] ——, "A tool for meaning driven materials selection," *Materials & Design*, vol. 31, no. 6, pp. 2932–2941, 2010.

[24] M. Wiberg, "Methodology for materiality: interaction design research through a material lens," *Personal and Ubiquitous Computing*, vol. 18, no. 3, pp. 637–649, 2014.

[25] E. Giaccardi and E. Karana, "Foundations of materials experience: An approach for HCI," in *Proceedings of SIGCHI Conference on Human Factors in Computing Systems*, 2015, pp. 2447–2456.

[26] C. Segalin, A. Perina, M. Cristani, and A. Vinciarelli, "The pictures we like are our image: Continuous mapping of favorite pictures into self-assessed and attributed personality traits," *IEEE Transactions on Affective Computing*, vol. 8, no. 2, pp. 268–285, 2017.

[27] "Flickr material database," 2018. [Online]. Available: https://people.csail.mit.edu/celiu/CVPR2010/FMD/

[28] C. Spence, "Crossmodal correspondences: A tutorial review," *Attention, Perception, & Psychophysics*, vol. 73, no. 4, pp. 971–995, 2011.

[29] P. Walker, B. J. Francis, and L. Walker, "The brightness-weight illusion. Darker objects look heavier but feel lighter," *Experimental Psychology*, vol. 57, pp. 462–469, 2010.

[30] L. Sharan, R. Rosenholtz, and E. H. Adelson, "Accuracy and speed of material categorization in real-world images," *Journal of Vision*, vol. 14, no. 9, p. 12, 08 2014.

[31] R. W. Fleming, "Material perception," *Annual Review of Visual Science*, vol. 3, pp. 365–388, 2017.

[32] E. H. Adelson, "On seeing stuff: the perception of materials by humans and machines," *Proceedings of the SPIE, Human Vision and Electronic Imaging VI*, vol. 4299, 2001.

[33] H. Nagano, S. Okamoto, and Y. Yamada, "Haptic invitation of textures: Perceptually prominent properties of materials determine human touch motions," *IEEE Transactions on Haptics*, vol. 7, no. 3, pp. 345–355, 2014.

[34] V. U. Ludwig and J. Simner, "What colour does that feel? tactile visual mapping and the development of crossmodality," *Cortex*, no. 49, pp. 1089–1099, 2013.

[35] L. Wastiels, H. N. J. Schifferstein, A. Heylighen, and I. Wouters, "Red or rough, what makes materials warmer?" *Materials and Design*, vol. 42, pp. 441–449, 2012.

[36] H.-N. Ho, D. Iwai, Y. Yoshikawa, J. Watanabe, and S. Nishida, "Combining colour and temperature: A blue object is more likely to be judged as warm than a red object," *Scientific Reports*, vol. 4, p. 5527, 2014.

[37] H.-C. Sun, A. E. Welchman, D. H. F. Chang, and M. Di Luca, "Look but don't touch: Visual cues to surface structure drive somatosensory cortex," *Neuroimage*, vol. 128, pp. 353–361, 2016.

[38] K. Isbister, K. Höök, J. Laaksolahti, and M. Sharp, "The sensual evaluation instrument: Developing a trans-cultural self-report measure of affect," *International Journal of Human-Computer Studies*, vol. 65, pp. 315–328, 2007.

[39] P. M. A. Desmet, "Measuring emotions: development and application of an instrument to measure emotional responses to products," M. A. Blythe, A. F. Monk, K. Overbeeke, and P. C. Wright, Eds. Springer, 2004, pp. 111–123.

[40] P. M. Bentler, "Linear systems with multiple levels and types of latent variables," in *Systems under indirect observation: Causality, structure, prediction*, K. G. Joreskog and H. Wold, Eds., 1982, pp. 101–130.

[41] ——, "Structural modeling and psychometrika: An historical perspective on growth and achivements," *Psychometrika*, vol. 51, pp. 35–51, 1982.

[42] S. A. Mulaik, L. R. James, J. V. Alstine, N. Bennett, S. Lind, and C. D. Stilwell, "Evaluation of goodness-of-fit indices for structural equation models," *Psychological Bulletin*, vol. 105, no. 3, pp. 430–445, 1989.

[43] D. Hooper, J. Coughlan, and M. Mullen, "Structural equation modelling: Guidelines for determining model fit," *Electronic Journal of Business Research Methods*, vol. 6, no. 1, pp. 53–60, 2008.

[44] R. P. McDonald and M.-H. R. Ho, "Principles and practice in reporting structural equation analyses," *Psychological Methods*, vol. 7, no. 1, pp. 64–82, 2002.

[45] J. B. Kruskal, "Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis," *Psychometrika*, vol. 29, pp. 1–27, 1964.

[46] ——, "Nonmetric multidimensional scaling: A numerical method," *Psychometrika*, vol. 29, pp. 115–129, 1964.

[47] R. Etzi, C. Spence, M. Zampini, and A. Gallace, "When sandpaper is 'kiki' and satin is 'bouba': an exploration of the associations between words, emotional states, and the tactile attributes of everyday materials," *Multisensory Research*, vol. 29, no. 1–3, pp. 133–155, 2016.

[48] Y.-T. Chen and M.-C. Chuang, "The difference of imagery perception between visual and tactile sensation," *International Journal of Affective Engineering*, vol. 14, no. 3, pp. 233–240, 2014.

[49] G. K. Essick, F. McGlone, C. Dancer, D. Fabricant, Y. Ragin, N. Phillips, T. Jones, and S. Guest, "Quantitative assessment of pleasant touch," *Neuroscience and Biobehavioral Reviews*, vol. 34, pp. 192–203, 2010.

[50] A. Klöcker, C. Arnould, M. Penta, and J.-L. Thonnard, "Rasch-built measure of pleasant touch through active fingertip explorations," *Frontiers in Neurorobotics*, vol. 6, no. 5, 2012.

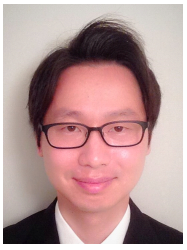
[51] S. R. Bhatta, K. Tiippana, K. Vahtikari, M. Hughes, and M. Kyttä, "Sensory and emotional perception of wooden surfaces through fingertip touch," *Frontiers in Psychology*, vol. 8, p. 367, 2017.

[52] H. Nagano, S. Okamoto, and Y. Yamada, "Visual and sensory properties of textures that appeal to human touch," *International Journal of Affective Engineering*, vol. 12, pp. 375–384, 2013.
[53] M. Shitara, H. Yoshida, M. Kamijo, G. Fujimaki, and H. Yamaguchi, "Hand movements used to assess the comfortability and likability of wood," *International Journal of Affective Engineering*, vol. 17, no. 1, pp. 49–56, 2017.
[54] A. Klöcker, M. Wiertlewski, V. Th'eate, V. Hayward, and J.-L. Thonnard, "Physical factors influencing pleasant touch during tactile exploration," *Plos one*, vol. 8, no. 11, p. e79085, 2013.
[55] E. Karana, B. Barati, V. Rognoli, and A. Z. van der Laan, "Material driven design (MDD): A method to design for material experiences," *International Journal of Design*, vol. 9, no. 2, 2015.
[56] "Oxford dictionaries," 2018. [Online]. Available: https://en.oxforddictionaries.com/
[57] R. Frost and S. Bentin, "Processing phonological and semantic ambiguity: Evidence from semantic priming at different soas," *Journal of Experimental Psychology: Learning Memory and Cognition*, vol. 18, no. 1, pp. 58–68, 1992.
[58] J. L. McClelland, *The case for interactionism in language processing*, ser. Attention and performance, 1987, vol. 12, pp. 3–36.
[59] M. Hisano, "Advances and issues in lexical ambiguity research," *Bulletin of the Faculty of Education, University of Tokyo*, vol. 33, pp. 107–115, 1993.
[60] T. Marinis, "Cross-modal priming in bilingual sentence processing," *Bilingualism: Language and Cognition*, vol. 21, no. 3, pp. 456–461, 2018.
[61] T. H. Carr, C. McCauley, R. D. Sperber, and C. M. Parmelee, "Words, pictures, and priming: on semantic activation, conscious identification, and the automaticity of information processing," *Journal of Experimental Psychology: Human Perception and Performance*, vol. 8, no. 6, pp. 757–777, 1982.
[62] W. Köhler, *Gestalt psychology (2nd ed.)*. Oxford, 1947.
[63] B. Lyman, "Representation of complex emotional and abstract meanings by simple forms," *Perceptual and Motor Skills*, vol. 49, no. 3, pp. 839–842, 1979.
[64] C. H. Liu and J. Kennedy, "Symbolic forms and cognition," *Psyke & Logos*, vol. 14, pp. 441–456, 1993.
[65] G. L. Collier, "Affective synesthesia: Extracting emotion space from simple perceptual stimuli," *Motivation and Emotion*, vol. 20, no. 1, pp. 1–32, 1996.
[66] A. Salgado Montejo, J. Alvarado, C. Velasco, C. Salgado, K. Hasse, and C. Spence, "The sweetest thing: the influence of angularity, symmetry, and the number of elements on shape-valence and shape-taste matches," *Frontiers in Psychology*, vol. 6, p. 1382, 2015. [Online]. Available: https://www.frontiersin.org/article/10.3389/fpsyg.2015.01382
[67] K. Taguchi, M. Hashimoto, K. Tobitani, and N. Nagata, "An estimation method of human impression factors for objects from their 3D shapes using a deep neural network," in *IS&T International Symposium on Electronic Imagin*, 2018, p. 194.
[68] M. Ziat, C. A. Balcer, A. Shirtz, and T. Rolison, *A century later, the hue-heat hypothesis: Does color truly affect temperature perception?*, ser. Lecture Notes in Computer Science. Springer, 2016, vol. 9774, pp. 273–280.
[69] J. Simner and V. U. Ludwig, "The color of touch: A case of tactile-visual synaesthesia," *Neurocase*, vol. 18, no. 2, pp. 167–180, 2012.
[70] S. Kobayashi, "The aim and method of the color image scale," *Color Research & Application*, vol. 6, no. 2, pp. 93–107, 1981.
[71] F. Camargo and B. Henson, "Aligning affective responses with fabric features of vehicle seat: An approach using the rasch measurement model," *International Journal of Affective Engineering*, vol. 14, no. 3, pp. 193–202, 2015.
[72] B. Petreca, B.-B. N., S. Baurley, P. Watkins, and D. Atkinson, "An embodiment perspective of affective touch behaviour in experiencing digital textiles," in *Proceedings of Humaine Association Conference on Affective Computing and Intelligent Interaction*, 2013, pp. 770–775.
[73] Y. Sakano and H. Ando, "Effects of head motion and stereo viewing on perceived glossiness,," *Journal of Vision*, vol. 15, no. 9, p. 15, 2010.
[74] S. Okamoto, H. Nagano, and Y. Yamada, "Psychophysical dimensions of tactile perception of textures," *IEEE Transactions on Haptics*, vol. 6, no. 1, pp. 81–93, 2013.
[75] Y. Vardar, C. Wallraven, and K. J. Kuchenbecker, "Fingertip interaction metrics correlate with visual and haptic perception of real surfaces," in *Proceedings of IEEE World Haptics Conference*, 2019, pp. 395–400.

Shogo Okamoto acquired his Ph.D. in informatics from Tohoku University in 2010. Currently, he is an associate professor at Nagoya University, Japan. His research interests include haptics, assistive systems, man-machine interfaces, and affective engineering.

Kohta Wakamatsu received a M.S. degree from Toyohashi University of Technology in 2019. Currently, he is a Ph.D. candidate.

Shigeki Nakauchi received a Ph.D. in engineering from Toyohashi University of Technology in 1993. He is currently a professor at Toyohashi University of Technology, Toyohashi, Japan.



Jinhwan Kwon received a Ph.D. in science from Tokyo Institute of Technology in 2015. He worked as a researcher at the Tokyo Institute of Technology and the University of Electro-Communications in 2017. He is currently working as a lecturer at Kyoto University of Education. His research interests are human informatics and intelligence science.

Maki Sakamoto acquired a Ph.D. from the University of Tokyo in 2000. Since 2015, she has been a professor at the University of Electro-Communications, Chofu, Japan.