



MATERIAL PERCEPTION AND MATERIAL IDENTIFICATION IN PRODUCT DESIGN

Dacleu Ndengue, Jessica; Juganaru-Mathieu, Mihaela; Faucheu, Jenny
MINES Saint-Étienne, France

Abstract

What makes designs intuitive? One essential part of it has to do with perception. The human body retrieves and processes information about its immediate surroundings at two levels: physical and perceptual. From the material engineer point of view, when a person interacts with a product, he (or she) interacts with the product and the materials simultaneously. The understanding of the perception mechanism of material's surfaces provides leverage for the perceived quality of products. Our study focuses on the influence of the object identification context on the perception of materials, i.e. a context where the materials are embedded in an identified object or a context where the materials are presented as anonymous parts. These findings can be used in product design in that user experience can be tuned by promoting congruity between function, materials and object identity to favor understandability of the product. On the contrary user's surprise can be promoted by favoring incongruity between these parameters.

Keywords: Requirements, Multisensory product experience, Human behaviour in design

Contact:

Jessica Dacleu Ndengue
MINES Saint-Étienne
centre SMS
France
jessica.dacleu@emse.fr

Please cite this paper as:
Surnames, Initials: *Title of paper*. In: Proceedings of the 21st International Conference on Engineering Design (ICED17),
Vol. 8: Human Behaviour in Design, Vancouver, Canada, 21.-25.08.2017.

1 INTRODUCTION

With the Industrial Revolution, technology somehow led innovation and product success during the 19th century. In the last few decades, a new industrial strategy is settling: pushed by market globalization, innovation is not restricted to technological innovation. New product specifications such as ergonomics, sensory characteristics, aesthetics, and personalisation, have become fully associated to the product or service design process. They contribute to the strategically important paradigm of “brand identity” and “experience design” or “interaction design” concepts. These parameters define the relationship level between the user and the product. In particular, sensations can lead to an emotional interaction that could highly impact, positively or negatively, the perceived quality of a product. Well designed, sensory attractive products can generate strong user-product relationships. This can extend a product’s lifetime decisively as a too early replacement is prevented, thus reducing energy and material consumption, a core factor in ecodesign and sustainability strategies (Tischner et al., 2000; Kawazu et al., 2000).

What makes designs intuitive? One essential part of it has to do with perception. The human body retrieves and processes information about its immediate surroundings at two levels: physical and perceptual (Stokes et al., 2015). At the physical level, our peripheral nervous systems gather information using a number of different nerve types each of which is sensitive to a particular type of stimulus. All the information gathered by the peripheral nervous system is conveyed through the central nervous system to the brain. There, the information is interpreted: it is the perceptual level. It is not sufficient for a good design to be rational and logical. Great, intuitive designs are those that allow us directly, and correctly, to see what we can do with a thing. Direct perception of possibilities for action is, essentially, what the concept of affordance (Norman, 1988) is about. The concept of affordances was quickly adopted in interaction design in order to make everyday things more intuitive and, in general, more usable.

From the material’s engineer point of view, when a person interacts with a product, he (or she) interacts with the product and the materials simultaneously. The understanding of the perception mechanism of material’s surfaces provides leverage for the perceived quality of products. In a review, Whitaker (Whitaker et al., 2008) highlighted that perception is strongly influenced by our cognitive abilities. As a parallel, Bushnell and Baxt (1999) showed that young children obtained poor cross-modal performance relative to intra-modal performance for shape recognition when the stimuli were unfamiliar (e.g., rubber knob, computer connector). By contrast, when familiar objects were used (toy car, pencil), tactile, visual and cross-modal recognition were all nearly perfect. Thus the mechanism of identification, of both the product and the material, strongly impacts the overall perception of a product. Bushnell and Baxt (1999) suggested that two different processes might be available for cross-modal recognition:

- Perceptually based processes may involve a specific perceptual experience. In this first process, the perceptual equivalence requires that vision and touch function in a similar way¹, such that the same type and quantification of information can be derived from the feel and from the visual appearance of an object property. For instance, if we touch a surface object without vision being engaged and we feel a specific degree of roughness, then by sight alone we should be able to perceive the same degree of roughness. This process only requires that vision and touch function similarly.
- Conceptually based processes may involve conceptual representations in long-term memory. In this second process, both modalities function similarly so that information derived from one sense can be communicated or transferred to the other. For instance, if we perceive a surface object by sight only, then we will be able to recognize it among other surface objects in a dark room using our sense of touch only. This means that information derived from vision was relevant and sufficiently meaningful for touch. This process implies that the senses be able to function together, in such a way that information can be passed and compared between the modalities (Marks, 1978).

According to Bushnell and Baxt (1999), these two processes are elicited, respectively, when unfamiliar and familiar objects serve as stimuli in cross-modal recognition tasks. Many studies on texture perception have used artificially produced stimuli such as sand paper, raised-dot pattern, etched surfaces. Whitaker et al. (2008) argued in a review that research using familiar object/textures, as opposed to “artificial textures”, benefit from the integration across senses due to more cognitive aspect rather than basic sensory encoding.

Human perception is inherently multisensory (Helbig and Ernst, 2008): we perceive the world simultaneously with multiple senses. Information that is perceived through different pathways can be

qualitatively different: the senses can provide either complementary or redundant information. Redundant sensory signals provide information about the same sort of object property and are represented in a common frame of reference, for example vision and touch provide redundant information about size and shape. In contrast, vision and taste provide complementary information about the identity of the object. In general we benefit from integrating multiple sources of information. Combining complementary sources of information is advantageous because it extends the range and variety of what can be perceived from one sense in isolation and can reduce perceptual ambiguity. Furthermore integrating multiple sensory sources usually leads to improved perceptual performance, more precise judgements and enhances detection of stimuli. Temporal synchrony and spatial coincidence are strong cues indicating whether or not two signals refer to the same object and so should be integrated into a combined percept. The brain integrates object information from multiple sensory systems to form a unique representation of our environment. Spatial separations can lead to a decline of visual-haptic integration (Gepshtein et al., 2005). Helbig and Ernst (2007) tested whether prior knowledge that two signals arise from the same object can promote integration even when the signals are spatially discrepant. Their findings suggest that prior knowledge about object identity can promote integration, even when information from vision and touch is provided at spatially discrepant locations. These findings can be used in product design in that user experience can be tuned by promoting congruity between function, materials and object identity to favor understandability of the product. On the contrary user's surprise can be promoted by favoring incongruity between these parameters. Our study focuses on the influence of the object identification context on the perception of materials, i.e. a context where the materials are embedded in an identified object or a context where the materials are presented as anonymous parts.

2 MATERIALS AND METHODS

2.1 Material's identity

The collective memory is populated by “familiar materials embedded in familiar objects” such as stone walls, wooden furniture, wool mattresses, iron swords, golden crowns. In these stereotypes, the names of materials seem to be charged with broader meanings. These names give the object cultural weight and solidity. Stone is durability, wood symbolizes the passage of time, wool is the warmth of intimacy, and steel is cold force. For many centuries, wood has been used and transformed by man to manufacture objects and structures. Through this slow accumulation, the field of possibilities of material was defined, man internalized wood's characteristics into group culture (Manzini, 1989). Wood has thus become a familiar material, endowed with recognizable identity. The same is true of all materials employed traditionally. Objects of the most recent generation appear even more frequently in a guise that allows us to say what they seem to be made of, but we cannot say what they really are made of. In this study, two sets of samples were analyzed. A set of « Objects (O) » comprises 12 smartphone cases (numbered from 1 to 12) bought in an online store in 2015 (Figure 1). Different colors, materials, textures are represented, the size of all smartphone cases is the same for all.



Figure 1. Picture of « Objects »

Table 1 shows the descriptions provided by the seller and the selling prices. The words used in these seller's descriptions were categorized into five categories: function identification, generic attributes, artificial material attributes, genuine material attributes and identification attributes. This table shows different strategies for the description of the products. In particular, these descriptions illustrate the identification strategy carried by the materials within these products. Some products are identified through genuine materials (O4, O8, O11) or materials (genuine or artificial) with an identified surface (O2, O5). Other materials are identified as artificial materials mimicking another material (O1, O6, O9, O12). Finally, some products are not identified through the materials they are made of, they are described using generic attributes (O3, O5, O7, O10).

Table 1. Description of « Objects »

Ref.	Description from seller's website (French)	selling price (€)	Function identification	Material identification (translated in English)			
				Generic attributes	Fake genuine material attributes	Genuine material attributes	Identification attributes
O1	Etui Rabat Bleu façon Autruche pour iPhone 5/5S PURO modèle Safari	24.90	Flip Case	Blue	Ostrich Style		
O2	Coque pour iPhone 5/5S Aspect cuir Rose matelassé	10.71	Case	Pink	Leather Aspect		Quilted
O3	Coque iPhone 5/5S verte rigide grainée	3.90	Case	Green, Stiff, grained			
O4	Coque pour iPhone 5/5S bois Cerisier	22.90	Case			Cherry wood	
O5	Coque iPhone 5 bleue croissillons souple, brillante	5.90	Case	Blue, flexible			diamond-shaped, glossy
O6	Coque pour iPhone 5/5S Rose en silicone Aspect cuir et Découpe logo	12.90	Case	Pink, Silicone	Leather Aspect		
O7	Bumper Antichoc pour iPhone 5/5S noir/jaune	9.40	Shockproof	Black/yellow			
O8	Coque iPhone 5/5S carbone ULTRA	26.90	Case			Carbon	
O9	FERRARRI Coque pour iPhone 5/5S Carbone Blanche Argent Logo Métal	29.90	Case	White	Carbon, Silver	Metal (Logo)	
O10	Coque de protection iPhone 5/5S blanche rigide grainée	3.90	Protective case	White, Stiff, grained			
O11	Coque iPhone 5/5S Carbone SPACE avec découpe Logo Apple	24.90	Case			Carbon	
O12	Coque iPhone 5/5S Effet Fibres de Carbone GRIFFIN	19.90	Case		Carbon Fiber Effect		

The second set of samples (« Anonymous materials (A) ») comprises 12 round-shaped samples (5 cm diameter) obtained by cutting a piece out of the smartphone covers Figure 2. Both sets comprise the same materials but in set “O”, the material is embedded in an object with an identified function while in set “A”, the material is presented as a sample of material.



Figure 2. Picture of « Anonymous materials »

2.2 Collecting and visualizing perception of materials

Behavioral experiments are used in cognitive psychology and psychophysics to collect the behavioral responses to different stimuli in order to understand how those stimuli are processed by the brain. On the other hand, behavioral experiments are also used in sensory evaluation (Valentin et al., 2016) to collect the responses to different stimuli in order, this time, to characterize the perception characteristics of the stimuli. Thus, while differing in terms of objectives, some of the methods used in these two fields are rather similar. In particular, projective mapping is a rather old technique in Psychology (Coombs, 1964) (but appearing under different names in the literature). By contrast, its use is relatively recent in sensory evaluation (Risvik et al., 1994). In projective mapping, assessors are asked to position on a large sheet of paper the products according to the products' similarities and dissimilarities. Projective mapping serves as a simple and quick technique to obtain product inter-distances (King et al., 1998; Risvik et al., 1997). These methods are loosely based upon the psychological construct of categorization, a concept

that formalizes the cognitive function of spontaneously organizing the world in meaningful and important natural categories or in categories statistically derived from the correlational structure of objects' properties and features. As far as sensory evaluation is concerned, however, the very large literature on categorization and concepts boils down to indicating that categorization requires little effort (i.e., it is mostly automatic) and that it occurs very early in life. Practically, this indicates that tasks based on simple categorization can be performed by untrained participants (including children) as well as by trained assessors and experts. In particular, Napping (Pagès et al., 2010). is a method derived from projective mapping that can be used with untrained assessors in which data are analyzed using Multiple Factor Analysis (MFA) available in the open source package *SensomineR* (Lê and Husson, 2008) developed under the R environment. The assessor has to position the samples across a limited two-dimensional surface (“nappe” means tablecloth in French). Ten to fifteen samples can be submitted simultaneously to each assessor. When all samples are placed, the assessors are asked to express their perception by associating a textual description of samples or sample clusters. The assessors have to do this according to their own criteria, those that are significant for them. There are no good or bad answers. The method was originally and mainly used for food and drink products (Pagès et al., 2010) but has also been used for sensory evaluation materials (Faucheu et al., 2015). It is easy to set up and rather quick. One test requires about ten to fifteen minutes and eight to ten assessors for the results to be to be significant.

In our experiment 23 assessors participated in the Napping experiment. They had different profiles (engineering students, lecturers, researchers, technical and administrative staff, PhD students). The experiment comprised two sequences. In the first sequence, the “A” sample set was evaluated. Then, the second sequence was dedicated to the « O » sample set. It was asked to the assessors to position samples that are perceived similar close together, and those which are different far away from each other. After positioning the samples, the assessors were asked to give attributes that qualify their perception of the texture of each sample or group of samples. The assessors were asked to slide the samples over the table without lifting them but no restriction was made on the tactile motion.

As a result, for each sample set, individual maps associated with descriptive words were collected for each assessor. The numerical data related to the positions of the various samples on the individual maps were analyzed using multiple factorial analyses (MFA) with the *SensomineR* and *FactomineR* packages available under R. From the MFA analysis of individual maps, a mean representation of the samples among all assessors is extracted which balances the influence of each participant in the global analysis. Various clustering methods (Han et al., 2011), like Hierarchical Clustering, enable to extract the clustering characteristics based on the mean representation.

3 RESULTS AND DISCUSSION

3.1 Statistical analysis of the numerical data

The mean representations visualize similarities (and dissimilarities) between samples when the assessor was in interaction with the samples. Our study focuses on the perception of the materials, either when the materials embedded in an identified object (O) or when the materials are presented as anonymous parts. By comparing the mean representations for O and A sample sets, insights on the influence of the object identification context on the perception of materials can be revealed. Qualitatively, the mean representations for O and A samples show similarities. In particular, samples 3, 6 and 10 are clustered in both mean representations. Similarly, samples 8, 9 and 11 are also clustered. The other samples are more individually positioned. However, their relative positions and distances are very similar. It can be also noticed that clusters [3;6;10] and [8;9;11] are far from each other.

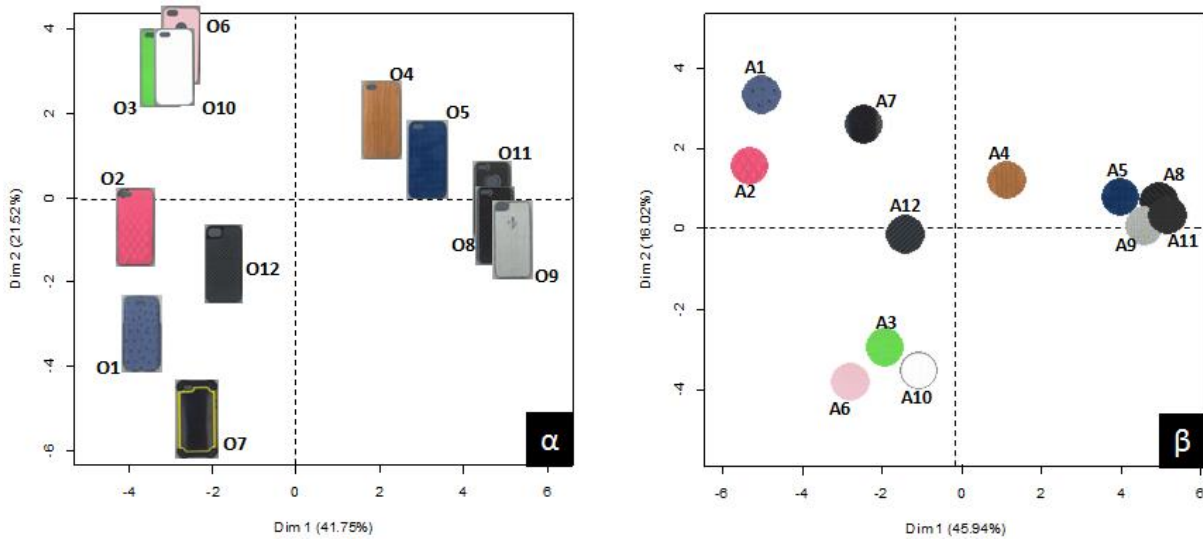


Figure 3. Mean representations for O samples (α) and A samples (β) in the space of the two first eigenvectors

In statistics, the RV coefficient is a parameter that evaluates the relationship between two sets of variables and it is based on the principle that two sets of variables are perfectly correlated if there exists an orthogonal transformation that makes the two sets coincide. Values of RV coefficients are comprised in the $[0;1]$ range, with a value close to 1 meaning that the two data sets considered are very similar. This RV coefficient is used here to evaluate the similarity between the mean representations of each sample sets. When comparing A and O mean representations, the RV coefficient is very close to 1 (RV coefficient = 0.93, p-value = $3.79 \cdot 10^{-5}$) meaning that the two mean representations are very similar which confirms the qualitative insights.

In order to visualize distances between samples positioned on the mean representation, a hierarchical clustering was performed. In this approach, the idea is to apply a stepwise algorithm which merges two objects at each step, the two which have the least dissimilarity. The result is a tree that visualizes the steps of the merging into clusters from individual objects to one unique cluster containing all objects. This is consistent with the previous conclusion in that both mean representations are very similar. Finally, based on the analysis of the numerical data from the mean representation, this suggests that the two sets of samples are globally perceived similar. Hereafter, the results of the analysis of the textual data are presented.

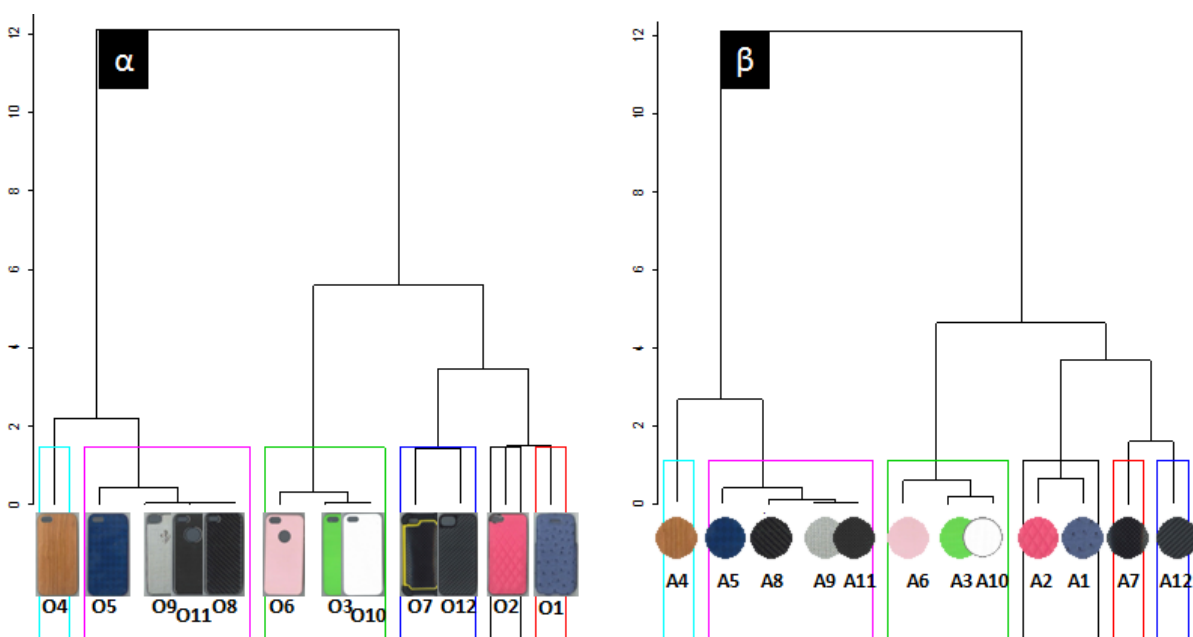


Figure 4. Hierarchical clustering from numerical datasets (mean representations) from

3.2 Statistical analysis of the textual data

As mentioned previously, descriptors were provided by assessors during the experiments. Assessors were told to provide words or groups of words they felt adequate to describe either an individual sample or clusters. A descriptor made of a group of words was kept as is (for example the group of word slightly slick became the descriptor slightly_slick). In the following analysis (Feldman and Sanger, 2007), the whole list of descriptors was analyzed without further changes. The textual data were organized into a table. The entries for the lines are the assessors name and the entries for the columns are the sample's reference. Two tables were created, one for the O samples and the other for the A samples. A third table was created by gathering the two first ones. 130 different and distinct descriptors were collected for the O samples. 137 different descriptors were collected for the A samples. And 240 different descriptors were obtained after merging the two lists.

To perform analysis on distances between samples characterized only by words, each material was described using a vector in the space of the ordered list of descriptors (130 dimensions for the O samples, 137 dimensions for the A samples and 240 dimensions for the O+A samples). Then, the vector corresponding to a sample is built with frequencies of each descriptor in the list of all words associated of the sample. A mathematical distance between two vectors (data1 and data2) is then defined as follow:

$$\text{dist}(\text{data1}, \text{data2}) = 1 - (\cos(\text{data1}, \text{data2}) + 1)/2 \quad (1)$$

where \cos is the cosine function

Using this definition of the distance between samples, a hierarchical clustering was performed. Note that if both vectors have the same coordinates then the distance is 0 and if both vectors are orthogonal then the distance is 0.5. Under these conditions, the proximity between two samples is given by distance values close to 0 while large distances have values close to 0.5.

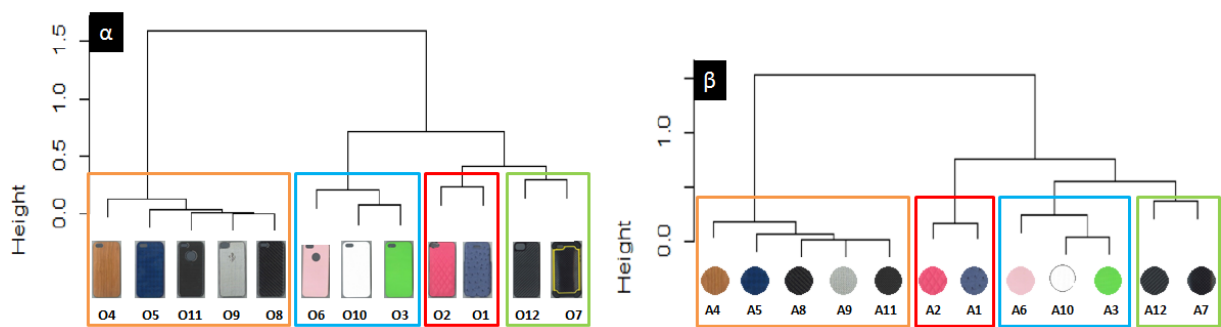


Figure 5. Hierarchical clustering of the textual data for the O samples (α) and the A samples (β)

The hierarchical trees obtained based on the textual data (Figure 5) show that the hierarchical clustering provides the same final partition. This suggests that the samples are perceived in a similar manner when presented embedded in an object or anonymously. These hierarchical clustering trees are also consistent with the conclusions of the numerical data analysis (Figure 4).

When considering the large dataset of 240 descriptors obtained after merging the two sub-datasets of descriptors from O samples and A samples, the textual data gives a novel opportunity to analyze perception. Indeed, for a given material, the influence of the object identification context can be highlighted by the calculation of the distance between the two sub-datasets within the large dataset. These distances are represented in Figure 6. The same definition of distances has been used, so proximity is represented by distances close to 0 and large distances are represented by distances close to 0.5. Finally, based on these distances, samples #2, #3, #6, #10 and #12 exhibit a large difference in perception with the object identification context while samples #4, #5, #8, #9 and #11 are perceived similarly.

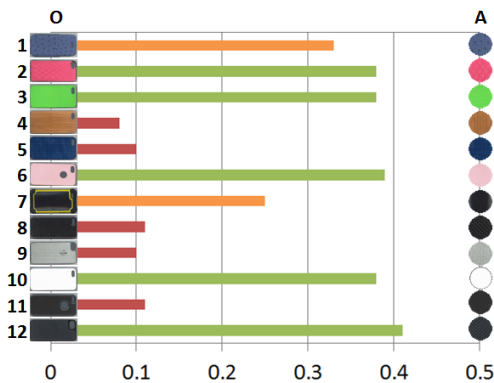


Figure 6. distances between sub-datasets O and A within the large dataset O+A

These results are compared to the description strategy adopted by the seller (Table 1). This comparison suggests that samples made of genuine materials with strong identity such as carbon fibers (#8, #11) and wood (#4) are not sensitive to the object identification context. On the other hand, materials that have a poor identity are more sensitive to the object identification context (#3, #10). Products made of fake genuine materials appear to be sensitive to the object identification context (#1, #2, #6, #12).

4 CONCLUSION

Our study focuses on the influence of the object identification context on the perception of materials, i.e. a context where the materials are embedded in an identified object or a context where the materials are presented as anonymous parts. The methods used in this study derive from behavioural and sensory experiments. It appears that genuine materials with strong identity are similarly perceived when explore under anonymous conditions or embedded in a product. On the other hand, fake genuine materials presented in a product appear to be perceived differently compared to the same materials presented as standard anonymous piece of materials. As a perspective of this work, the textual data will be further investigated under semantical approaches to refine the conclusions. Moreover, this study raises questions on the use of genuine and artificial materials as leverage of the perceived value of products.

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ACKNOWLEDGMENTS

This work was supported by the LABEX MANUTECH-SISE (ANR-10-LABX-0075) of Université de Lyon, within the program "Investissements d'Avenir" (ANR-11-IDEX-0007) operated by the French National Research Agency (ANR).