

Article

Investigation of Japanese Onomatopoeia *Tsuru-Tsuru* as a Suitable Sensory Attribute for Perception of Surface Properties of Textiles by Non-Trained Individuals

Raphael Romao Santos, Nozomi Katayama and Sachiko Sukigara *

Department of Advanced Fibro Science, Graduate School of Science and Technology, Kyoto Institute of Technology, Matsugasaki, Sakyo-ku, Kyoto 606-8585, Japan

* Correspondence: sukigara@kit.ac.jp

Abstract: In recent years, using non-trained individuals in sensory science for analytical tasks has gained traction. Identifying attributes enabling non-experts to express perceptions is crucial for accurate fabric assessments and effective communication of product properties to consumers. This study explored the potential utility of the Japanese onomatopoeia *tsuru-tsuru* as a sensory attribute for evaluating fabric surface properties. Two experiments were conducted. The first ranked 16 samples to identify those eliciting the *tsuru-tsuru* sensation, exploring its relationship with attributes like smoothness and coolness. The second involved a detailed descriptive sensory evaluation of selected samples, examining the relationship between *tsuru-tsuru*, coolness, slipperiness, and hardness. Fabric preferences assessment and cluster analysis were also employed to understand individual differences in perception. Sensory assessments revealed *tsuru-tsuru*'s comparable performance with attributes like smoothness and slipperiness, facilitating effective sample distinction. Participants showed high agreement, indicating shared perceptions. Preferences favored fabrics with *tsuru-tsuru* qualities. The clustering analysis revealed participants had slightly different interpretations of *tsuru-tsuru*. Overall, results indicated the positive potential value of *tsuru-tsuru* in describing textile surfaces for non-trained individuals.



Citation: Romao Santos, R.; Katayama, N.; Sukigara, S. Investigation of Japanese Onomatopoeia *Tsuru-Tsuru* as a Suitable Sensory Attribute for Perception of Surface Properties of Textiles by Non-Trained Individuals. *Textiles* **2023**, *3*, 438–453. <https://doi.org/10.3390/textiles3040026>

Academic Editor: Andrea Zille

Received: 21 October 2023

Revised: 22 November 2023

Accepted: 23 November 2023

Published: 28 November 2023

Keywords: textiles; sensory profiling; surface properties; onomatopoeia; ranking analysis; descriptive analysis; individual differences; clustering

1. Introduction

In sensory analysis, identifying relevant sensory attributes is crucial for effectively describing the sensory characteristics of textile fabrics, especially in the context of descriptive sensory analysis conducted by non-trained individuals. Recently, there has been increasing interest in utilizing non-trained individuals for analytical tasks in sensory science [1]. The identification of sensory attributes that allow non-experts to articulate their perceptions is essential for obtaining accurate descriptive assessments of fabrics. Moreover, it enables textile manufacturers to communicate the properties of their products to consumers in a purposeful, efficient, and understandable manner.

Sensory attributes can be categorized into three layers in increasing order of abstraction [2]. These layers consist of attributes within the perceptual psychophysical layer, those within the affective layer, and finally, those within the preference layer. Attributes within the perceptual layer are typically encountered in classical descriptive sensory assessments and include features closely related to the physical properties of fabrics measured in the laboratory. Examples of such attributes include smoothness, coolness, hardness, and more. On the other hand, the affective and preference layers are more closely related to consumer-oriented features, reflecting daily consumer experiences. These include attributes like richness, cleanliness, elegance, comfort, and various others.



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

The abstraction gap in these layers presents significant challenges not only in communicating fabric qualities to consumers but also in incorporating consumers into analytical sensory applications. Consequently, there is a need for sensory attributes that exist in the middle ground, possessing semantics at both lower and higher levels of abstraction. An example of such attributes is those related to onomatopoeia. Onomatopoeia is frequently employed to express feelings or convey a sense of atmosphere [3], but they are also known for their ability to convey texture-related cognition [4,5].

This study explored the utility of onomatopoeia as a sensory attribute, using the Japanese onomatopoeic term *tsuru-tsuru* as an example. In Japan, onomatopoeia holds significant importance in daily communication and has garnered substantial attention from researchers in the field of natural language processing [3,6]. *Tsuru-tsuru* is a widely used onomatopoeia in Japan, typically associated with sensations of smoothness, slipperiness, and shininess [7]. *Tsuru-tsuru* can describe differences in texture sensation at a fine resolution [8] and is commonly used to describe the surfaces of various materials, including textile fabrics.

We hypothesized that *tsuru-tsuru* could serve as an effective attribute for describing the surface of textile fabrics in comparison to attributes traditionally employed in classical descriptive sensory analysis. Furthermore, *tsuru-tsuru* may be interpreted through the lens of classical attributes in the context of sensory assessment. For instance, it might be comprehended as a combination of smoothness and hardness, offering a more nuanced understanding of the sensory characteristics of textile surfaces.

It could be reasonably argued that for an attribute to be valuable in sensory assessments, two crucial requirements must be met: (1) the attribute should enable participants to distinguish between samples, and (2) there must be a reasonable level of agreement among participants regarding the attribute. This implies that participants should share similar perceptions and understanding of what the attribute means.

As a result, the study prioritized individual differences among participants, giving emphasis to their unique preferences and perceptions. Samples were used to interpret the participants' *tsuru-tsuru* perception, assessing the given attribute's ability to differentiate samples in their sensory space. Samples were carefully chosen to replicate a sensory environment familiar to consumers.

The study's scope was confined to the surface properties of the fabrics, aligning with the association of *tsuru-tsuru* with texture sensations. Data analysis reflected the emphasis on individuals, omitting mean calculations for attributes. This approach allowed for a more general interpretation, respecting the unique preferences and perceptions of each participant. Gender analysis was not pursued due to the small number of participants and inherent sensory variability among non-trained individuals, ensuring that the results represent commonalities irrespective of gender. It is worth noting that the samples used here are commonly used by both men and women.

To investigate the suitability of *tsuru-tsuru* as a sensory attribute, two experiments were conducted. First, a preliminary ranking sensory experiment (Experiment I) aimed to address the practical question of which types of samples evoke the *tsuru-tsuru* sensation. This experiment involved assessing 16 samples with diverse physical properties to identify those that conveyed the sensations of *tsuru-tsuru*. Additionally, the experiment explored the relationship between *tsuru-tsuru* and two other closely related attributes, smoothness, and coolness. Six samples were selected based on their ranking for *tsuru-tsuru* for further investigation.

In the second phase (Experiment II), the 6 previously selected samples underwent a comprehensive descriptive sensory evaluation, encompassing five attributes: *tsuru-tsuru*, smoothness, slipperiness, coolness, and hardness. The investigation delved into the relationship between *tsuru-tsuru* and the other attributes, relying on participant agreement and sample scores. Participants' fabric preferences were also evaluated to understand liking drivers based on the fabric's physical properties. Finally, clustering analysis was employed to assess individual differences in perception of *tsuru-tsuru* by the participants.

For specific data analysis methods employed here, please refer to the corresponding sections in the methods section. Information on the software used here is highlighted in Appendix A.2.

2. Methods: Experiment I—Ranking Sensory Evaluation

2.1. Samples

In the ranking experiment, sixteen samples were utilized. When selecting these samples, particular attention was paid to creating a diverse set, representing a sample sensory space that consumers would encounter in real-life scenarios, such as when shopping for apparel. The samples featured varying surface properties, including distinct fiber compositions and tactile qualities. Half of the samples were woven, while the other half were knitted. Samples No. 2 and No. 3 were composed of polyester fibers commonly used in summer underwear, often associated with the sensation of *tsuru-tsuru* in Japan. Photographs of the samples are displayed in Figure 1, and basic specifications are provided in Table 1.

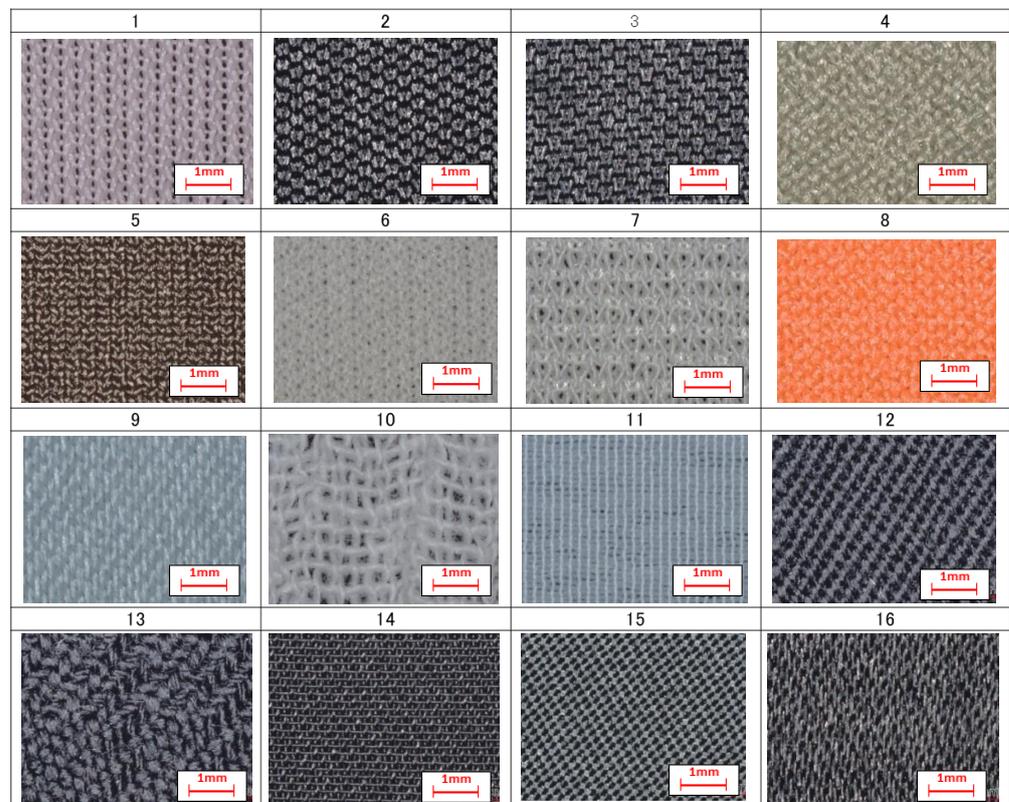


Figure 1. Photographs of the fabric samples taken under a microscope. Samples 1–8 were woven, and samples 9–16 were knitted. Samples No. 2 and No. 3, composed of polyester fibers, are frequently employed in summer underwear, commonly associated with the tactile sensation known as *tsuru-tsuru* in Japan.

The physical properties related to the surface characteristics of the samples were measured using the Kawabata Evaluation System for Fabrics (KES-F) [9]. Since our emphasis was on the participants, the sample sensory space considered in this study was limited by the space spanned by the physical properties of the fabrics.

Surface properties of the fabrics were measured along the warp and weft directions using KES-SE-SR and KES-SE surface testers (Kato Tech Co., Ltd., Kyoto, Japan). The compression properties were measured using KES-G5 (Kato Tech Co., Ltd., Kyoto, Japan). Tensile properties were measured along the warp and weft directions using the KES-FB1-AUTO-A tensile and shear tester (Kato Tech Co., Ltd., Kyoto, Japan). The maximum value of the heat flow (q_{\max} , W/cm²), related to the warm/cool feeling, was also measured

using the KES Thermo Labo II (Kato Tech Co., Ltd., Kyoto, Japan) following the JIS L1927 standard. All measurements were conducted under standard measurement conditions. In Appendix A, the total list of parameters used in the study can be seen in Table A1 together with the measurement conditions. Moreover, parameter values are listed in Table A2, and finally, plots of the parameters are available in Figure A1.

Table 1. Sample properties.

Sample No.	Fiber (%)	Yarn Density		Thickness (mm)	Weight (g/m ²)
knitted					
		wales/cm	courses/cm		
1	POM100	24.6	50.0	0.55	170
2	P100	23.6	27.9	0.44	220
3	P100	20.9	28.2	0.33	130
4	P89/Pu11	24.3	19.3	0.95	290
5	P86/Pu14	12.3	24.3	0.80	270
6	P100	22.5	18.6	0.43	75
7	P100	19.3	20.8	0.56	170
8	P85/Pu15	40.8	25.5	0.72	210
woven					
		ends/cm	picks/cm		
9	P100	14.1	51.6	0.69	150
10	C100	20.0	28.5	1.30	140
11	P100	73.5	44.4	0.25	80
12	W100	34.4	25.8	0.51	210
13	W100	21.1	24.9	0.49	210
14	P100	52.4	46.9	0.21	87
15	P77/C23	72.5	87.0	0.40	140
16	S50/C50	47.0	13.8	0.45	64

POM: Polyacetal, P: Polyester, Pu: Polyurethane, C: Cotton, S: Silk, W: Wool. Thickness was measured under a pressure of 49.0 Pa. using the KES-G5 compression tester (Kato Tech Co., Ltd., Kyoto, Japan).

The sample dimensions were 20 cm × 20 cm, typical dimensions for measuring the physical properties of samples using the KES-F system. These dimensions strike a good balance between machine measurement convenience and textile handle during sensory evaluation.

2.2. Participants

Twenty-five university students (14 men and 11 women) took part in the ranking experiment. All participants were in their 20s with normal color vision and normal or corrected-to-normal visual acuity.

2.3. Ranking Sensory Evaluation

The fabric samples were simultaneously presented to each participant, who was then instructed to rank them in descending order of intensity based on the following sensory attributes: (1) *tsuru-tsuru*, (2) smoothness, and (3) coolness. The samples were randomized and placed on a well-lit, flat table. Each ranking assessment took place separately for each attribute. No specific instructions were provided on how to touch or handle the fabrics, allowing participants to evaluate the samples freely. Importantly, no two samples received the same ranking from any participant. The experiment was carried out in one day, in the afternoon, with room temperature ranging from 21 °C to 24 °C.

2.4. Data Analysis: Ranking Sensory Evaluation

2.4.1. Data Set

The shape of the 3-way matrix containing the ranking results was structured with samples as rows, attributes as columns, and participants as slices, Figure 2. The matrix was unfolded based on the Tucker-1 method [10] along the columns. The transformation was represented as

$$X_{i,j,k} \rightarrow X_{i,jk} \quad (1)$$

and illustrated in Figure 3.

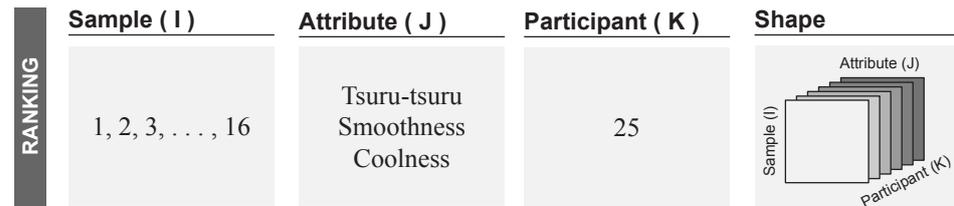


Figure 2. Data set used in the ranking sensory analysis

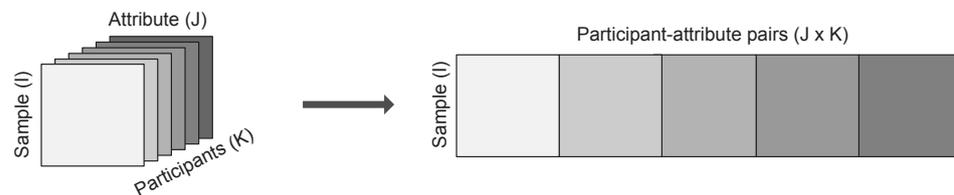


Figure 3. Tucker-1 matrix unfolding. The 3-way matrix is unfolded horizontally into a 2-way matrix. The new columns represent participant-attribute pairs.

In the ranking experiment, a decision was made to analyze each attribute j separately, where $j = 1, 2, 3$. This approach enabled the assessment of the relationship among the samples for each attribute in isolation. This process yielded 3 matrices, each with samples as rows and participant-attribute pairs $j \times K$ as columns. The new columns represented each attribute as perceived by each participant separately. The Tucker-1 method keeps all the sensory information in the data set without resorting to averages, thus preserving individuality.

2.4.2. Principal Component Analysis (PCA)

Principal Component Analysis was individually applied to each of the 3 unfolded matrices to assess the relationships among samples and the agreement (consensus) among participants, represented by the scores and loadings, respectively. More specifically, correlation loadings were used to represent the agreements. Correlation loadings involve a simple normalization procedure that facilitates the comparison of different PCAs. They measure the correlation between the original variables and the principal components generated by the PCA. To aid in visualizing these correlations, an outer ellipse corresponding to 100% correlation and an inner ellipse corresponding to 50% correlation were also plotted. The data was not normalized.

The PCA model was given by:

$$X_{i,jk}^{(j)} = T_{i,n} P_{jk,n}^T + E_{i,jk} \quad (2)$$

where $X^{(j)}$ was one of the 3 sensory matrices, T the score matrix, P the loadings matrix and E the residuals matrix. The index n was the number of principal components. The correlations loadings, defined by the correlation between the columns of X and T (respectively, X_{jk} and P_n) was given by:

$$R_{jk,n}^{(j)} = \text{Corr}(X_{jk}, T_n) \quad (3)$$

2.4.3. Selection of Samples for Descriptive Sensory Analysis

Six samples were selected from the ranking experiment based on their ranking in *tsuru-tsuru*, while to a lesser extent, consideration was given to the ranking on the remaining attributes. The fiber material and structure were also considered.

3. Methods: Experiment II—Descriptive Sensory and Preference Evaluations

3.1. Samples

Six samples were selected from the ranking experiment, considering variations in both warp and weft weaves, resulting in a total of 12 specimens. Participants were then instructed to run their fingers along the samples. The motivation behind this was to reduce the influence of other touch-related factors and emphasize the examination of the fabric's surface properties. To accommodate this change in the experimental design, the surface area of the samples was increased, and their dimensions were adjusted to 10 cm × 60 cm. Each sample was affixed to cardboard (approximately 3 mm thick) to prevent movement. This measure was also motivated by the aim to minimize the influence of other touch-related factors.

3.2. Participants

Thirty-two participants (24 men and 8 women) in their 20s, with normal color vision and normal or corrected-to-normal visual acuity, took part in the experiment.

3.3. Descriptive Sensory Evaluation

Participants slid their fingertips across the length of the 12 specimens and were asked to rate each fabric according to 5 sensory attributes on a 6-point scale from 0 to 5. In the scale, the zero point indicated the absence of the given attribute. The attributes included: (1) *tsuru-tsuru*, (2) smoothness, (3) slipperiness, (4) coolness, and (5) hardness. The manner in which each participant touched the samples was not specified, except that they should slide their finger along the length of the sample from left to right five times. The order of presentation of the samples was randomized. The experiment was carried out over various weeks at different times of the day, with room temperature ranging from 21 °C to 24 °C.

3.4. Preference Evaluation

To assess preferences and drivers of liking during the descriptive evaluation, participants were asked to score the samples for their liking on the same scale, ranging from 0 through 5, for each of the 12 specimens.

3.5. Data Analysis: Descriptive Sensory Evaluation

3.5.1. Data Set

The structure of the data set was similar to the ranking experiment, except that now the J sensory attributes corresponded to the 5 descriptive attributes (see Figure 4). The 3-way matrix was unfolded, considering all the attributes at once, resulting in one wide matrix with rows corresponding to samples and columns corresponding to $J \times K$ participant-attribute pairs. Two-way ANOVA, with samples and participants as effects, was performed on each sensory attribute individually to test its significance. All attributes were significant, and results were not reported.

3.5.2. Principal Component Analysis (PCA)

Principal component analysis was applied to the unfolded sensory matrix to assess the relationship among the samples and the agreement among the participants. Due to the large number columns in the matrix, the correlation loadings plot was repeatedly plotted each time with one of the the attributes highlighted. The data was not normalized. Similarly to Section 2.4.2, the model was given by:

$$\mathbf{X}_{i,jk} = \mathbf{T}_{i,n} \mathbf{P}_{jk,n}^T + \mathbf{E}_{i,jk} \quad (4)$$

and

$$R_{jk,n} = \text{Corr}(X_{jk}, T_n) \tag{5}$$

where X and R are single matrices.

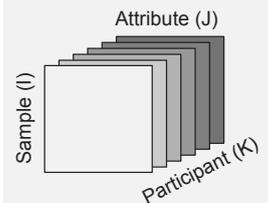
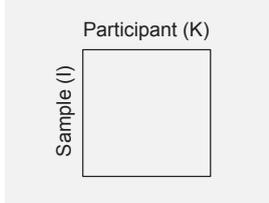
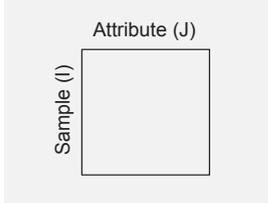
DESCRIPTIVE	PREFERENCE	PHYSICAL PROPERTY
Sample (I)		
1, 2, 3, 11, 15, 16 warp and weft 12 specimen	1, 2, 3, 11, 15, 16 warp and weft 12 specimen	1, 2, 3, 11, 15, 16 warp and weft 12 specimen
Attribute (J)		
Tsuru-tsuru Smoothness Coolness Slipperiness Hardness	Liking	MIU MMD SMD WC LC RC qmax T W
Participant (K)		
32	32	–
Shape		
		

Figure 4. Data set used in the second experiment

3.6. Data Analysis: Preference Evaluation

3.6.1. Data Set

The liking data were structured as a two-way matrix, with rows representing samples and columns representing the liking scores assigned by each participant. The physical properties used to evaluate the drivers of liking were organized as a two-way matrix, with rows representing samples and columns representing the physical properties. Both data sets were standardized due to differing units. The data sets are depicted in Figure 4.

3.6.2. Internal Preference Mapping

Internal preference mapping [11] involved applying PCA to the liking data and subsequently regressing the physical properties onto the principal components. This approach follows the standard application of Principal Component Regression (PCR) [12]. It’s important to note that the regression model did not include an intercept term because both data sets were centered during the process. The regression was applied using the first five principal components, with the goal of achieving a total explained variance equal to or greater than 80%. The PCR model was given by (1) PCA of the preference data set

$$X_{i,k} = T_{i,n}P_{k,n}^T + E_{i,k} \tag{6}$$

and (2) the physical properties regressed onto the Score T

$$y_i^{(j)} = T_{i,n}q_n + f_i \tag{7}$$

where y is the vector representing the j th physical parameter, q is the vector of regression coefficients, f is the vector of regression residuals, and n is the number of principal com-

ponents. q is also referred to as regression loadings, as it assumes the same role as P in Equation (6).

3.7. Data Analysis: Clustering

Here, we investigated the fact that the interpretation of *tsuru-tsuru* may vary among individual participants. Hierarchical clustering was applied to the correlation loadings matrix as calculated in Section 3.5. The correlation loadings matrix, which describes the relationship among original attributes in terms of the principal components, was used to calculate the cosine distance (Equation (8)) between *tsuru-tsuru* and the remaining attributes for each participant individually (see Figure 5). The calculations were based on the first five principal components ($n = 5$). The resulting matrix consisted of participants as rows and the cosine distances from *tsuru-tsuru* to the four attributes as columns. Hierarchical clustering was applied to this matrix using ward linkage and Euclidean distance as a metric, resulting in the formation of four distinct clusters.

$$1 - \frac{\mathbf{R}_i \cdot \mathbf{R}_{j'}}{\|\mathbf{R}_i\| \cdot \|\mathbf{R}_{j'}\|} \quad (8)$$

where \mathbf{R}_i represent the correlation loadings for *tsuru-tsuru* and $\mathbf{R}_{j'}$ for the remaining attributes.

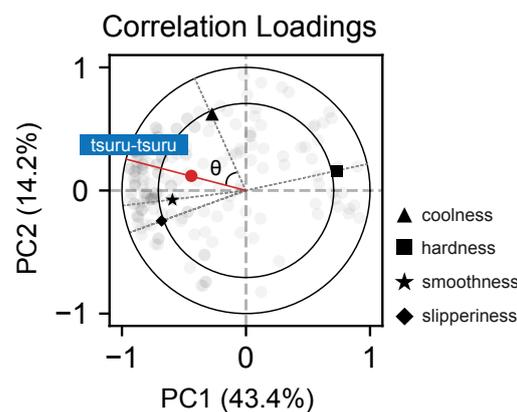


Figure 5. The regression loadings matrix (Equation (5)) was used to calculate the cosine distance between *tsuru-tsuru* and other attributes. Plot shows regression loadings with Participant 1 highlighted.

4. Results and Discussion

4.1. Experiment I

4.1.1. Ranking Sensory Evaluation

The scores show that participants ranked the samples similarly in all attributes (see Figure 6, top row). Moreover, the high level of agreement displayed in the correlation loadings plots (see Figure 6, bottom row), together with the high explained variance for the first two principal components, strongly suggests a similar perception of the samples and a shared understanding of the attributes. There is somewhat weaker agreement for the attribute coolness. A noticeable polarization in agreement (top-bottom) is observed in the loadings plots regarding the second principal component. Overall, it could be argued that the diversity in physical properties of the samples might have made the ranking task less challenging for the participants.

4.1.2. Sample Selection

Samples 1, 2, 3, 11, 15, and 16 were chosen based on the overall ranking in *tsuru-tsuru*, but also considering the other two attributes. Samples No. 2 and No. 3 were given precedence, given they are commonly used in summer underwear, often associated with the sensation of *tsuru-tsuru* in Japan.

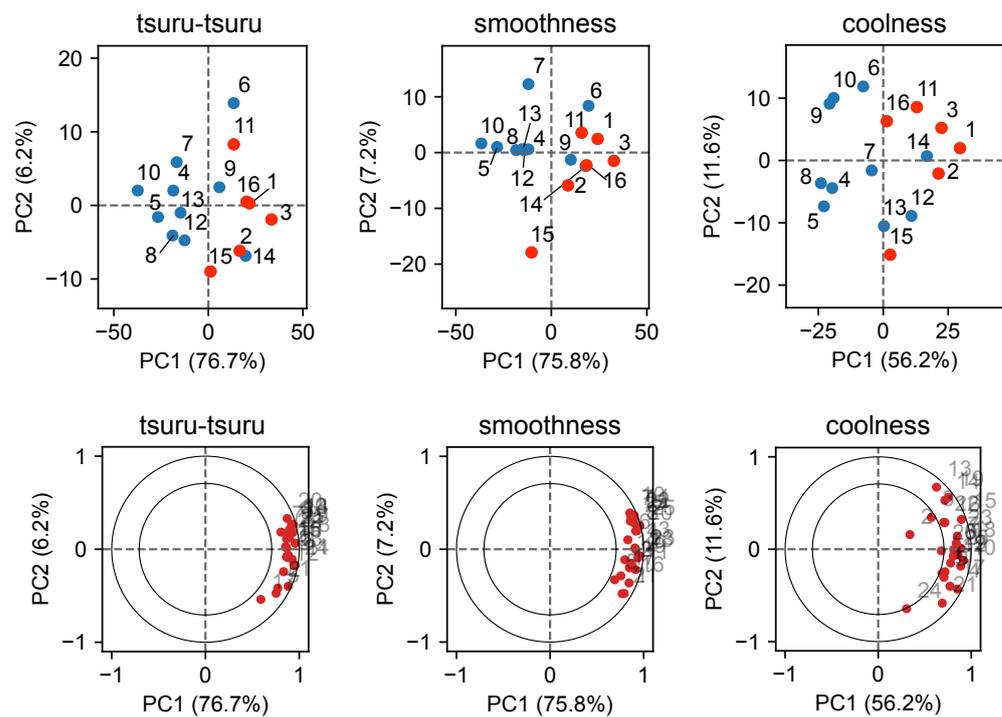


Figure 6. (Top row) Scores and (bottom row) correlation loadings from the ranking experiment. The scores represent the relationship among the samples as ranked by the participants. Red markers on scores plots represent samples chosen for the descriptive analysis. The correlation loadings depict the agreement among participants.

4.2. Experiment II

4.2.1. Descriptive Sensory Analysis

The score plot (see Figure 7b) shows an interesting polarization regarding the warp and weft directions. This polarization is supported by the physical properties illustrated in Figure 8.

The sample selection from the ranking experiment resulted in very smooth samples. In practice, the samples were much harder to distinguish by touch compared to the previous experiment. Examining the agreement among participants (see Figure 7c), despite the challenge of distinguishing between samples, significant consensus is observed for *tsuru-tsuru* and smoothness, although slightly less for slipperiness. Agreement for coolness is notably low. In the case of hardness, there is less agreement among participants, but it notably explains the polarization between warp and weft in the scores plot. Smooth samples are on the left, and the hard samples are on the right. This observation is intriguing, considering the samples were mounted on a considerably thick cardboard substrate and could not move. Despite this, participants successfully detected hardness with relative consensus, highlighting their sensitivity to this attribute. By now, the results suggested that *tsuru-tsuru* was a good drop-in replacement for the attribute smoothness and possibly slipperiness.

4.2.2. Preference Evaluation

The scores plot (Figure 9a) shows similar relationships among samples as observed in the descriptive evaluation, including the same polarization in the warp/weft directions. This suggests that participants prefer samples with properties of *tsuru-tsuru*. The regression loadings (Figure 9c) show participants prefer samples with low values of LT and SMD (first principal component). The second principal component indicates about half of the participants prefer samples with high q_{max} and low MIU and WT, while the other half prefers the opposite. This explains the same (top/bottom) polarization (Figure 9b) as seen in the descriptive evaluation. This suggests *tsuru-tsuru* to have weak connotations of coolness. The results also suggest that the interpretation of *tsuru-tsuru* is participant-dependent. For

example, participants who prefer high qmax and low MIU may interpret *tsuru-tsuru* as a mixture of slipperiness and coolness.

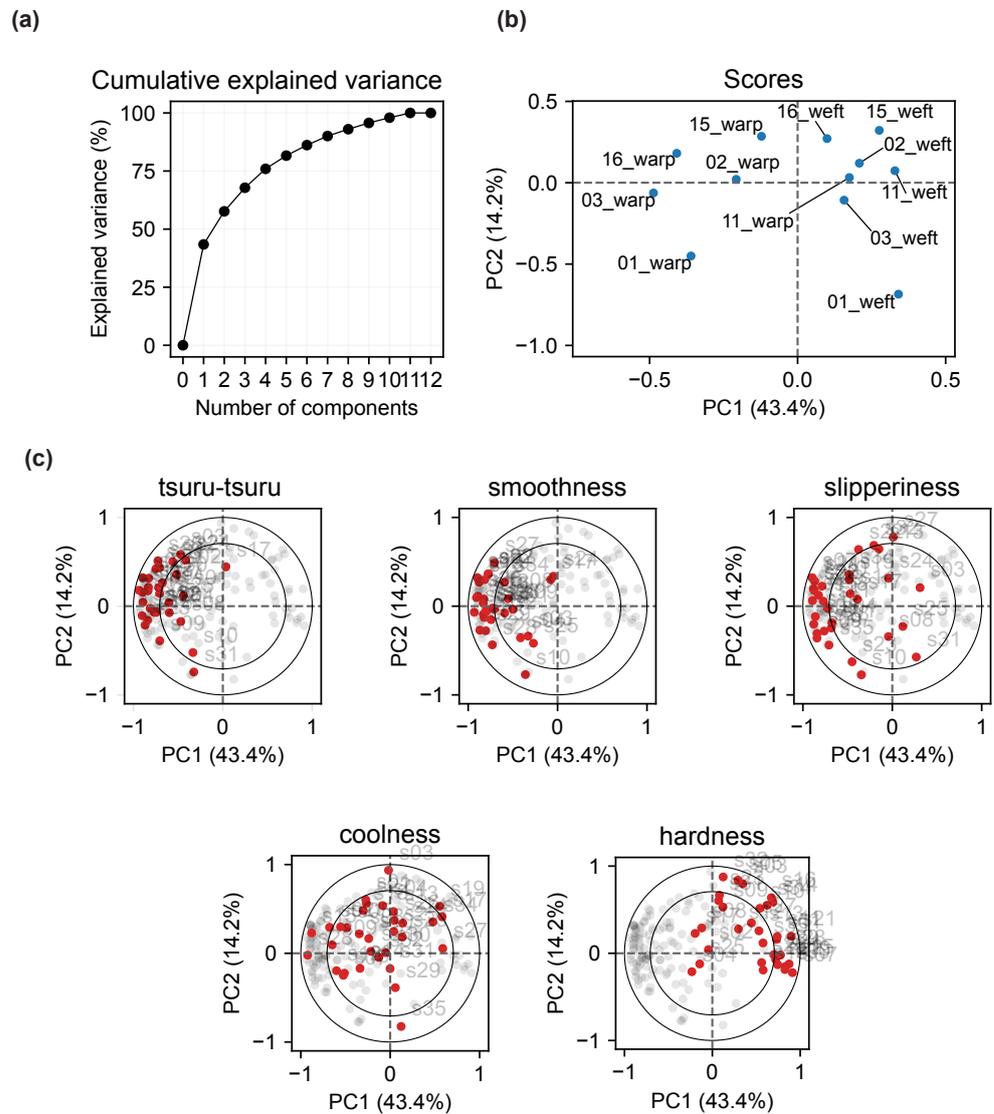


Figure 7. (a) Cumulative explained variance, (b) scores and (c) correlation loadings for the descriptive sensory experiment. The same correlation loadings plot is shown multiple times, with each attribute highlighted individually (red markers), while the markers for the other attributes are dimmed. This representation is particularly helpful in visualizing the level of agreement for each sensory attribute.

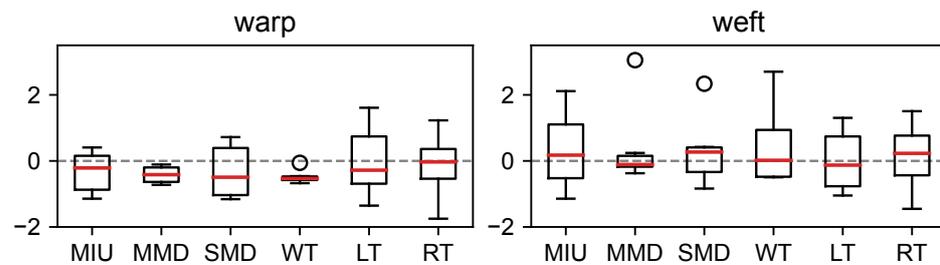


Figure 8. Box plot of standardized physical properties. Overall, the warp direction exhibits smaller values for physical properties that are direction-dependent.

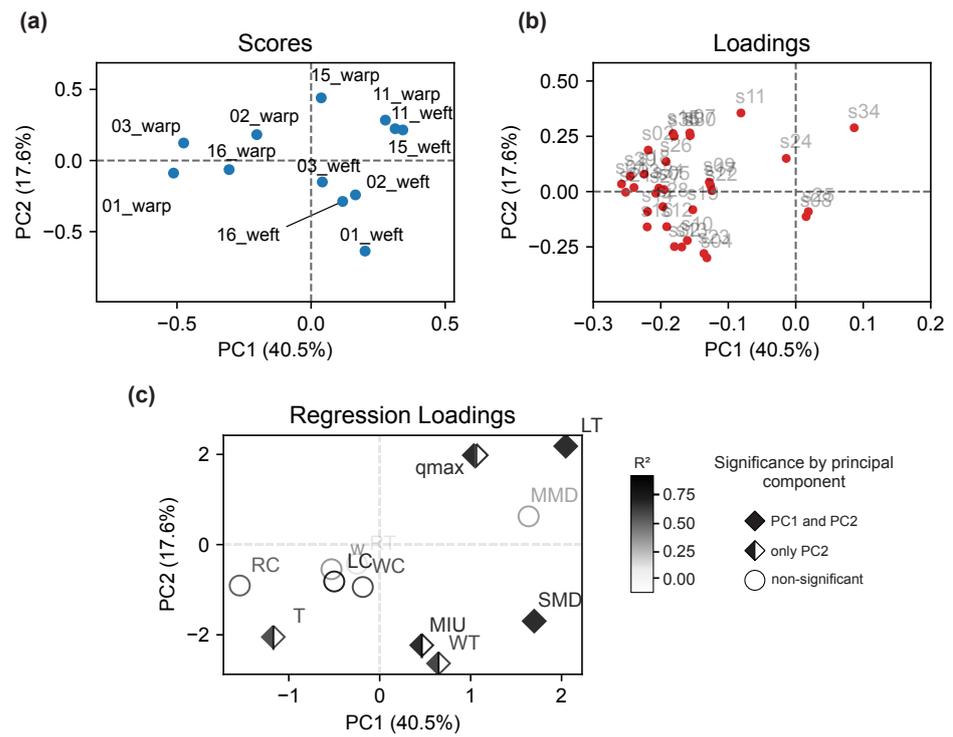


Figure 9. Principal component regression. (a) Scores, (b) loadings, (c) regression of physical properties onto the first 5 principal components. The darkness of the marker corresponds to the magnitude of the explained variance (R^2). Significant attributes (p -value < 0.05) are depicted with either a full or half black fill. Markers lacking a fill were not significant. A full fill indicates significance in both principal components, while a half fill represents significance only in the second component.

4.2.3. Clustering

Clustering (Figure 10) shows some differences in the interpretation of *tsuru-tsuru*, with about 47% of the participants (C1) interpreting it as a mixture of mainly smoothness and slipperiness. The second-largest group (C4), comprising 25%, interpreted *tsuru-tsuru* mainly as smoothness. There was no relationship between clusters and the gender of the participants. It is worth highlighting the agreement for *tsuru-tsuru* throughout the experiments despite slightly different interpretations of what *tsuru-tsuru* is.

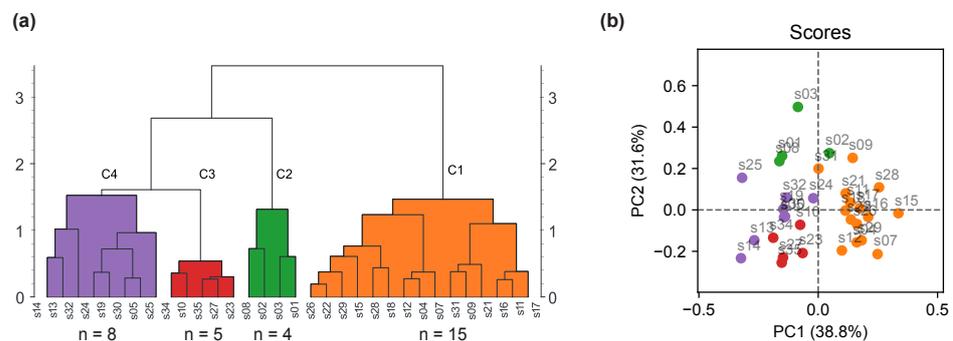


Figure 10. (a) Dendrogram depicting the results of the cluster analysis of the cosine distances between the attribute *tsuru-tsuru* and the attributes smoothness, slipperiness, coolness, and hardness using the first five principal components of the loadings matrix. (b) PCA was applied to the cosine distances matrix for easier visualization of clusters.

5. Conclusions

This study investigated the Japanese onomatopoeia *tsuru-tsuru* as a potentially useful attribute in the assessment of fabric surface properties by non-trained individuals in sensory

evaluation experiments. *Tsuru-tsuru* was compared to less abstract but more traditionally used attributes: smoothness, slipperiness, coolness, and hardness. The study encompassed two experiments: (1) a ranking sensory evaluation and (2) a descriptive sensory evaluation. The experiments assessed the participants' individual differences regarding the sample score and attributes. The participants' preferences were assessed. Clustering was carried out to investigate the participants' understanding/perception of *tsuru-tsuru* based on other attributes.

Overall, the sensory assessments showed that *tsuru-tsuru* (Figure 11) performed comparably with attributes like smoothness and slipperiness. *Tsuru-tsuru* allowed participants to properly distinguish samples, including features like weave direction. Participants demonstrated a high level of agreement when using *tsuru-tsuru*, implying that participants shared similar perceptions and understanding of what the attribute means.

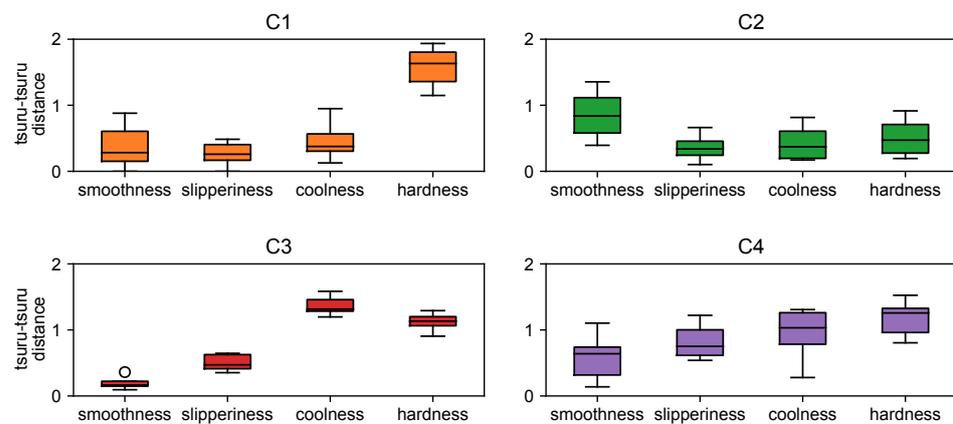


Figure 11. Box plot visualizations of each cluster. The y-axis indicates the cosine distance between *tsuru-tsuru* and the other attributes. Cosine distance values range between 0 and 2, with lower values indicating greater similarity.

Preference assessments indicated that participants liked fabric samples with the qualities of *tsuru-tsuru*. Moreover, results showed polarization in the preference for warm/cool feelings. The clustering analysis revealed that participants had slightly differing interpretations of *tsuru-tsuru* in relation to smoothness, coolness, slipperiness, and hardness.

Establishing good communication with consumers is a crucial aspect of fabric design. Attributes such as smoothness and hardness may not be clearly understood by consumers. These findings collectively highlight the potential value of *tsuru-tsuru* as an attribute for describing and assessing textile surface properties by non-trained individuals.

Author Contributions: R.R.S. designed and supervised the experiments, analyzed the data and drafted the manuscript. N.K. performed the experiments. S.S. guided and supplied feedback and commented on the final format of the paper. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

KES-F	Kawabata Evaluation System for Fabrics
MIU	Coefficient of Friction
MMD	Mean Deviation of MIU
SMD	Surface Roughness
LT	Linearity of Tensile
WT	Tensile Energy
RT	Tensile Resilience
LC	Linearity of Compression
WC	Compression Energy
RC	Compression Resilience
q _{max}	Maximum value of heat flux
PCA	Principal Component Analysis
PCR	Principal Component Regression

Appendix A

Appendix A.1. Fabric Sample Physical properties

Table A1. Characteristic values and standard conditions of measurement of the physical properties.

Property	Symbol	Characteristic Value	Unit	Measurement Condition
Compression	LC	Linearity of compression displacement curve	-	Maximum pressure, P _m = 5 kPa Rate of compression = 20 μm/s
	WC	Compression energy	J/m ²	
	RC	Compression resilience	%	
Tensile	LT	Linearity of tensile displacement curve	-	Maximum tensile load: 490 N/m Tensile speed = 0.2 mm/s
	WT	Tensile energy	J/m ²	
	RC	Tensile resilience	%	
Surface	MIU	Coefficient of friction	-	20 steel piano wires with 0.5 mm diameter and 10 mm length. Contact force = 0.49 N Steel piano wire with 0.5 mm diameter and 5 mm length. Contact force = 0.1 N
	MMD	Mean deviation of MIU	-	
	SMD	Geometrical roughness	μm	
Thickness	T ₀	Thickness at pressure of 49.0 Pa	mm	ΔT = 10 °C
Weight	W	Fabric weight per unit area	g/m ²	
q _{max}	q _{max}	Maximum value of heat flux	W/m ²	

Table A2. Physical properties measured using the KES-F system of machines.

Sample	LC	WC (J/m ²)	RC (%)	LT		WT (J/m ²)		RT (%)		MIU		MMD		SMD (μm)		qmax (kW/m ²)
				Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft	
1	0.56	0.10	44.90	0.67	0.64	1.53	7.89	51.43	57.29	0.32	0.56	0.004	0.007	0.76	3.68	0.18
2	0.38	0.05	41.46	0.69	0.74	0.51	2.80	57.06	58.12	0.27	0.37	0.004	0.014	0.73	1.96	0.23
3	0.50	0.06	57.11	0.61	0.72	0.60	4.17	59.18	51.53	0.25	0.45	0.003	0.010	0.63	1.20	0.20
4	0.33	0.13	43.09	0.95	1.06	14.38	14.91	72.24	82.92	0.43	0.43	0.007	0.013	2.10	2.54	0.13
5	0.37	0.14	54.09	1.02	0.96	3.69	5.76	79.08	64.73	0.33	0.40	0.012	0.013	2.83	2.37	0.15
6	0.49	0.13	42.05	0.72	0.79	2.39	13.10	62.90	43.30	0.41	0.43	0.005	0.006	0.77	1.64	0.13
7	0.54	0.11	46.79	0.64	0.68	2.15	6.36	65.01	54.15	0.29	0.35	0.009	0.015	1.87	2.63	0.16
8	0.41	0.13	50.54	1.01	1.09	20.75	10.57	69.90	81.60	0.34	0.45	0.024	0.013	1.22	2.34	0.15
9	0.44	0.20	45.12	0.76	0.75	0.54	3.47	64.25	75.35	0.48	0.64	0.006	0.008	1.79	2.49	0.11
10	0.42	0.58	37.54	0.83	0.67	1.22	5.41	57.58	58.33	0.32	0.39	0.035	0.028	4.58	2.53	0.09
11	0.48	0.07	37.97	0.90	0.84	0.36	0.61	43.60	62.68	0.34	0.25	0.009	0.046	2.27	2.01	0.20
12	0.20	0.11	56.61	0.78	0.86	1.91	0.95	92.30	92.70	0.33	0.28	0.008	0.010	1.96	1.97	0.22
13	0.27	0.10	52.70	0.79	0.79	0.97	2.93	82.12	87.32	0.20	0.28	0.009	0.008	2.34	2.09	0.20
14	0.51	0.03	50.07	0.69	0.74	0.57	0.18	44.19	64.62	0.16	0.19	0.009	0.010	0.96	0.79	0.25
15	0.20	0.09	37.31	0.84	0.87	0.11	0.52	64.83	45.73	0.14	0.14	0.010	0.009	1.66	0.91	0.26
16	0.17	0.11	38.80	0.74	0.65	0.32	0.54	54.65	66.81	0.15	0.21	0.009	0.010	2.09	1.79	0.18

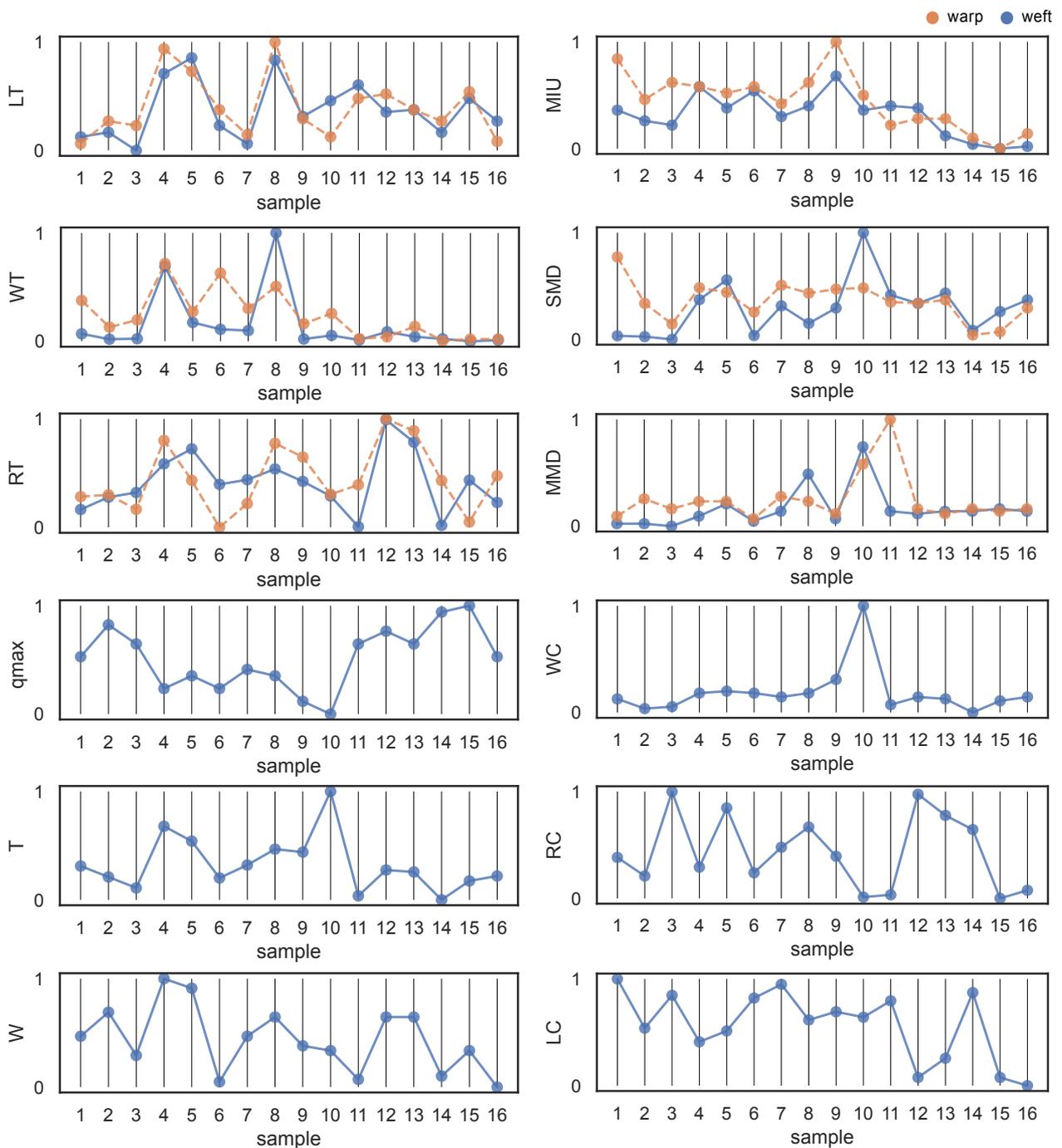


Figure A1. Fabric physical properties measured using the KES-F system. Parameters are normalized between 0 and 1.

Appendix A.2. Software

The analysis was carried out using Python version 3.11 as the base language. NumPy version 1.25.2 and Pandas version 2.0.3 were used for data manipulation. Matplotlib version 3.7.2 was used to generate the plots. For statistical analysis, Statsmodels version 0.14.0 was utilized. Principal Component Analysis (PCA) was conducted using statsmodels.api, PCR was conducted using statsmodels.api.PCA, and regression used statsmodels.api.OLS. Hierarchical clustering was performed using scipy.cluster.hierarchy from scipy version 1.11.3.

References

1. Ares, G.; Varela, P. Trained vs. consumer panels for analytical testing: Fueling a long lasting debate in the field. *Food Qual. Prefer.* **2017**, *61*, 79–86. [[CrossRef](#)]
2. Okamoto, S.; Nagano, H.; Ho, H.N. Psychophysical dimensions of material perception and methods to specify textural space. In *Pervasive Haptics: Science, Design, and Application*; Springer: Tokyo, Japan, 2016; pp. 3–20.
3. Komiya, K.; Kotani, Y. Classification of Japanese onomatopoeias using hierarchical clustering depending on contexts. In Proceedings of the 2011 Eighth International Joint Conference on Computer Science and Software Engineering (JCSSE), Nakhonpathom, Thailand, 11–13 May 2011; pp. 108–113.
4. Etzi, R.; Spence, C.; Zampini, M.; Gallace, A. 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 Res.* **2016**, *29*, 133–155. [[CrossRef](#)] [[PubMed](#)]
5. Ramachandran, V.S.; Brang, D. Tactile-emotion synesthesia. *Neurocase* **2008**, *14*, 390–399. [[CrossRef](#)] [[PubMed](#)]
6. Nagatomo, T.; Hiraki, T.; Ishizuka, H.; Miki, N. Unsupervised learning enables extraction of tactile information from text database. *IEEE Access* **2021**, *11*, 101155–101166. [[CrossRef](#)]
7. Toshihiro, W.; Skrzypczak, E.R.; Snowden, P. *Kenkyusha’s New Japanese-English Dictionary*, 5th ed.; Kenkyusha: Tokyo, Japan, 2003.
8. Yamagata, K.; Kwon, J.; Kawashima, T.; Shimoda, W.; Sakamoto, M. Computer Vision System for Expressing Texture Using Sound-Symbolic Words. *Front. Psychol.* **2021**, *12*, 654779. [[CrossRef](#)]
9. Kawabata, S. *The Standardization and Analysis of Hand Evaluation*, 2nd ed.; Textile Machinery Society of Japan: Osaka, Japan, 1980.
10. Tucker, L.R. The extension of factor analysis to three-dimensional matrices. In *Contributions to Mathematical Psychology*; Holt, Rinehart, and Winston: New York, NY, USA, 1964; pp. 109–127.
11. Jolliffe, I.T.; Morgan, B. Principal component analysis and exploratory factor analysis. *Stat. Methods Med. Res.* **1992**, *1*, 69–95. [[CrossRef](#)] [[PubMed](#)]
12. Næs, T.; Brockhoff, P.B.; Tomic, O. *Statistics for Sensory and Consumer Science*; John Wiley & Sons: Hoboken, NJ, USA, 2011.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.