2021 IEEE/SICE International Symposium on System Integrations (SII)
Iwaki, Fukushima, Japan. January 11 - 14, 2021

Hierarchical Modeling of Individual Tactile, Emotional, and Preferential Responses to Leathers using Bayesian Structural Equation Modeling*

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Abstract— **In order to increase the emotional value of products when being touched, it is important to be able to explain the relationship between physical phenomena given to end users and their perceptual and emotional responses and preferences. Although general methods in current modeling is multivariate analysis to the physical characteristics of material samples obtained from commercial measuring instruments, they do not address two kinds of variances entangled. First, the deviation is caused by individual differences in the finger's mechanical properties and hand motions to explore material surfaces. Second, the repetitive error of the answers is caused by the difficulty of the questionnaire survey. Therefore, we measured the physical (mechanical and thermal) phenomena between the leather material and the panelists actually touching the sample and added them to the explanatory variable. Then, using latent factors of structural equation modeling (SEM), the repetitive error of the questionnaire was attempted to be taken into account while modeling the hierarchical structure of low-order perceptions such as "soft" and "smooth" and higher-order emotional responses and preferences such as "luxury" and "comfortable." In the conventional SEM, in case the large estimation error is set on an observed variable, the calculation becomes unstable due to the local solution. In this study, we applied a method to stabilize calculation while considering a large error using the Bayesian SEM. This approach produced a semantically reasonable model that would help design leather products.**

I. Introduction

The automobile industry is undergoing a substantial change described as a once in every 100 years major transformation. The inevitability of this change is represented by CASE, which stands for *connected* (*C*), *autonomous* (*A*), *shared* (*S*), *and electric* (*E*). At Toyota Boshoku, *humanity* (*H*) has been added to CASE to define CHASE as an opportunity to connect products and services to human emotion and empathy and enhance the value they create, which is represented by the Quality of Time and Space slogan. As one of the methods to provide that value, it is necessary to be able to evaluate the perceptual/emotional responses and preferences of end users, such as luxury and comfort, using measurable indicators. The present study relates the physical characteristics of materials and the subjective responses about perception, emotion and preference they instill in users, focusing particularly on tactile sensation over the other four senses. This has typically been approached by applying multivariate analysis to the characteristics of the material samples obtained from commercially-available measuring instruments and the average of the corresponding results from panelists' questionnaires. Despite the many previous studies conducted in this field, unsolved problems remain. There are two problems with earlier approaches: 1) the reliability of the questionnaire is low, and 2) the causal relationship is not revealed by the multivariate model.

Here is an example expanding on the issue of the reliability of the questionnaire. In the past, we conducted a multivariate analysis on 15 samples of genuine and synthetic leather using the mechanical properties measured with commercial measurement instruments as explanatory variables (e.g. KES series, Kato Tech Co., Ltd.), and the questionnaire results from panelists as objective variables. The regression to the average value for the questionnaire had a high coefficient of determination of 0.878, but the regression to all responses for the questionnaire had a low coefficient of determination of 0.151. The problem with this approach is that it does not consider the individual differences in the responses to the questionnaire or in the contact between the panelists' fingers and the materials.

Many previous studies have used multiple regression models and have not aimed to identify causal relationships between variables. For example, even if a positive correlation between bending rigidity in a woven fabric and an impression of luxury is found, their causal relationship is not shown. In contrast, hierarchical modeling is used [1—5] to further explore causal relationships. In hierarchical modeling, for example, the following relationships are specified. A woven fabric with a lower bending rigidity feels softer. Softer fabrics feel more comfortable. Finally, a comfortable woven fabric is perceived to be luxurious. Such hierarchical relationships lead to an understanding of semantic causation. Nonetheless, whether they really show the cognitive relationship of perception, emotion, and preference of physical properties will be an object of debate for future studies. The present paper adopts a hierarchical modeling approach.

In light of the above problems, we developed a modeling method that incorporates the following two points. To our best knowledge, there is no modeling method solving these problems. First, most previous studies used commercial measurement instruments, but in order to explicitly consider the difference between panelists, we decided to measure the mechanical and thermal contact phenomena when they touch the material (Sec. II-A). Next, we investigated the consistency of the responses of the panelists themselves, and used the high consistency responses of the panelists. However, it was

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978-1-7281-7657-4/21/$31.00 ©2021 IEEE

impossible to reduce the error as much as expected. Bayesian SEM was adopted as a hierarchical modeling method to take the repetitive error of these questionnaires into account (Sec. II-B).

II. Data and Method

In the previous section, we noted that individual differences in finger conditions and hand motions have not been incorporated into the model. Further, the repetitive error in questionnaire has not been considered in the model. In this section, we describe solutions to address these issues.

A. Individual differences in finger conditions and touch behaviors

As mentioned above, most previous studies used commercial measurement instruments to obtain mechanical properties of samples, but we considered that the differences between hands and touch methods can be incorporated in the model as an explanatory variable by measuring the physical phenomena when a panelist actually touches the sample. For each panelist, ten random leather samples were picked at random from a selection of thirty leather samples (Table 1). Then, physical measurements and the questionnaire were conducted for blind-folded panelists. The physical phenomena measured, chosen by referring to tactile dimensions for textures [6], were the load-displacement property when the sample is pushed with the tip of the index finger, the temperature-time property of the finger and sample interface to acquire heat-transfer characteristics, as well as the vibration-frequency property when the fingertip slides over the sample, and friction-speed property (Stribeck characteristics) when the sample is stroked with the tip of the index finger. For measurement, we prepared a three-axis load meter, a two-dimensional laser displacement meter that measured the position of the finger, a small thermistor and an acceleration detector. The feature quantities were collected from the measured waveform data. However, the number of feature dimensions rose as high as 140, and then exploratory factor analysis was performed on each of the four measured physical stimulus waveforms, to reduce the number of dimensions to 21. By contract, some details cannot be disclosed, regarding the measurement equipment and feature dimensions.

B. Repetitive error due to difficulty of the questionnaire

In order to reduce the effects of the repetitive error of the questionnaire, we considered excluding the data of panelists who cannot determine tactile sensation with consistency from the analysis. First of all, we tried to improve the accuracy of the questionnaire by asking panelists working in the leather industry, who have many opportunities to come in contact with leather material on a daily basis. This might bias the data and eliminate the generality of the model. However, in this study, the range of panelists was narrowed down to lessen the repetitive errors in the questionnaire, because the errors, i.e, random variations, of the answers from in-house panelists was large in the pre-survey. In order to ensure the generality of the model, we need to collect data from various panelists in the future. The questionnaire consisted of a total of eighteen questions (Table 2) in a random order, with eight questions

Table 1. Classification of thirty leather samples

Material / Feature	Grained		Suede
	Shrink	Fine	
Genuine	8	7	4
Synthetic	4	4	3

Table 2. Questions on perception, emotion and preference

Perception	Emotion/Preference
-Soft +Hard	-Gorgeous +Concise
-Warm +Cold	-Elegant +Inelegant
-Resilient +Flexible	-Solemn +Relaxed
-Smooth +Rough	-Urban +Country
-Bumpy +Flat	-Cute +NotCute
-Scratchy +NotScratchy	-Friendly +Hostility
-With +W/O Tension	-Obedient +Stubborn
-Moist +Dry	-Young +Old
	-Luxury +Cheap
	-Conmfort +Uncomfort

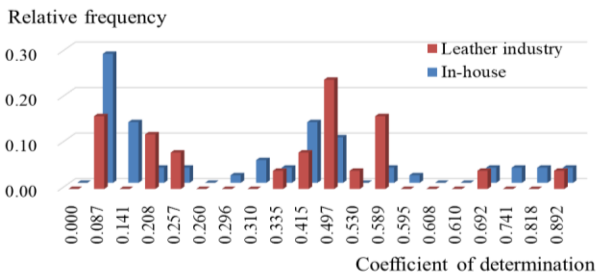

Fig. 1 Histgram of coefficients of determination as consistency of panelists' answers. The higher, the more consistent.

concerning the perception of physical properties ("soft-hard," "warm-cold," etc.) and ten questions addressing emotion and preference ("luxury-cheap," "cute-not cute," etc.), using the 7-point semantic differential method. During the questionnaire, we randomly presented specific samples twice without notifying the panelists, and received pair of responses to the same sample. Since the distribution of the coefficient of determination of these responses was divided in two peaks at 0.30 (Fig. 1), it was decided to use only the data from panelists with coefficient of determination above 0.30.

In addition, a structural equation model (SEM) was adopted as the hierarchical modeling method (using the R lavaan package [7]). The reason for that choice is that the causal relationship can be analyzed hierarchically using a path diagram, and modeling can be performed while taking repetitive error into account by setting latent factors. As mentioned in Section I, it is impossible to completely remove the repetitive error by selecting the data of the panelists with consistent answers. As shown in Fig. 1, even among professional panelists who regularly handle the material, it is rather rare for the panelists to ensure consistency in the task of scoring the tactile physical phenomena. For example, only 3% of all panelists have a coefficient of determination above 0.80.

Furthermore, in the SEM calculation built on the strict assumption that most of the variance in the observations is repetitive error, the search for the solution using the maximum

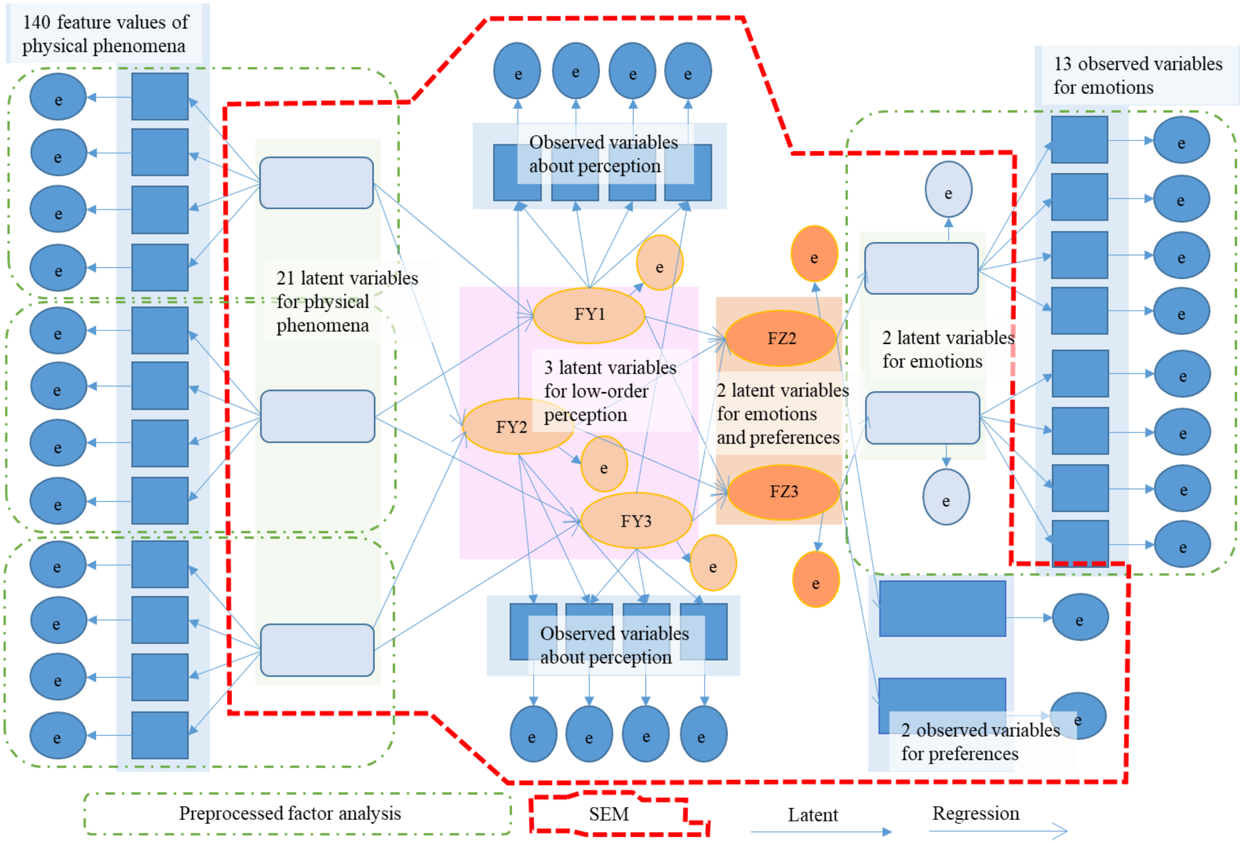

Fig. 2 Schematic diagram of SEM.

likelihood method tends to make regression error of specific node to converge to zero, path coefficients diverge and it outputs improper solution. Therefore, in this study, the parameters were estimated using a Bayesian SEM that can handle Markov chain Monte Carlo methods (MCMC), using the R blavaan package [8], [9]. Bayesian SEM differs from the maximum likelihood method used in ordinary SEM by generating proposed parameter through a Markov chain and adopting or rejecting them on the basis of likelihood. Repeating this operation and performing the Monte Carlo method, produces a histogram of adopted values (which constitutes the posterior probability distribution). Although the computational cost is high, this parameter estimation method does not get caught in the local minimum. In this study, we realized a robust hierarchical causal model by including latent factors in Bayesian SEM. This also makes it possible to account for the magnitude of the repetitive error obtained from the actual data in the analysis. As mentioned above, most previous studies did not incorporate mere repetitive error due to difficulty of the questionnaire. Instead, they used average answers from multiple trials or they did not retest the same sample for the same panelist.

C. Construction of 3-layered model

The SEM of this study has a three-layer structure in which the feature quantities of the physical phenomena are placed in the lower layer, the latent variables of the questionnaire results regarding low-order perception are placed in the middle layer, and the latent variables of the questionnaire results regarding emotion and preference are placed in the upper layer (Fig. 2).

In order to determine the placement of latent factors, an exploratory factor analysis was performed on the eight measured variables about perception in the middle layer, and based on a scree plot (a graph the eigenvalues of the covariance matrix plotted in descending order), we determined the number of latent factors to be three. The three factor scores and loadings were then calculated as in Table 3. After that, as a preliminary analysis for designing the path diagram, the above three factor scores were assigned to the middle layer, and a normal SEM analysis was performed without latent factors. The values of several fit indices were very good, and the accuracy of the model configuration was confirmed. Consequently, in order to incorporate the repetitive error of the questionnaire, the latent factors were inserted in place of the middle lower-order perceptual layer and the upper sensitivity and preference layer in the three-layer model built on this configuration. In the lower perceptual layer, the three latent factors correspond to the results of the exploratory factor analysis (Table 3) above.

In the upper emotion and preference group, the scores for the two factors of “gorgeous, elegant, solemn” and “cute, friendly, obedient” in the emotional questionnaire items were derived in advance and added to the model. The latent factors of “luxury” and “comfort” were defined as well using the same method (Fig. 3). We defined 0.200 (this value should be optimized in the future) as a provisional value smaller than the average error variance of 0.580 for the data in Fig. 1 as the error variance from these latent factors to the observed variables. Then, the maximum likelihood method was attempted to calculate this model. However, with a normal

SEM analysis, despite smaller assumed error variances than the estimated values by actual measurement, the regression error converged to zero and the coefficients of paths to node FZ2 "luxury" in the emotional and preference layer resulted in improper solutions. In order to perform similar parameter estimation with Bayesian SEM, this time from the blavaan package in conjunction with the JAGS software for the Gibbs sampling, that constitutes one of MCMC methods, burn-in was applied 1000 times, model adapting 1000 times, and iteration 10000 times to estimate each parameter.

III. Results

The parameter estimation converged with a model configuration that could not be solved by the maximum likelihood method as in Fig. 4. The maximum value of the potential scale reduction factor (PSRF) of the model was 1.055, which indicates the degree of convergence of the calculation for the difference between the three Markov chains. Generally, parameters converge when equivalent to 1.050. Thus, Bayesian SEM can model the complex relationship of tactile sensations that cannot be estimated by ordinary SEM while taking repetitive errors into account. The result of the analysis showed that the regression residual value of the luxury latent factor was 0.137, and the coefficient of determination was equivalent to 0.863. This model exhibits the accuracy close to the average value of the multivariate analysis in Section I.

We investigated each path coefficient to interpret the derived model. For example, the regression path coefficients for the latent factor of FY1 taken from the relationship between the lower physical layer and the perceptual layer, are shown in Table 4. For example, a positive coefficient from MR1 (normal force while sliding) and MR14 (normal force while pushing) to FY1 suggests that panelists applied larger normal forces for bumpier surfaces. In other words, by touching flat surface with smaller normal force, they might have avoided unpleasantness resulting from stick-slip phenomenon (alternatively repeating static and kinetic friction) and risk of damaging or wrinkling the material in their experience. Negative effects from MR2 (shearing force while sliding) and MR15 (coefficient of friction while sliding) on FY1 indicate that bumpier surfaces produced smaller friction. A positive effect MR5 (magnitude of vibration above 50 Hz) to FY1 indicates the vibration becomes large when getting over the roughness, and A positive effect MR9 (Kurtosis of linear regression residuals of vibration spectrum) to FY1 indicates the spectrum becomes peaky due to the periodicity of the unevenness. These coefficients are reasonably interpreted. We also checked path coefficients from the perceptual layer to emotional and preference layer (Table 5). Both "luxury" and "comfort" factors received the large effects from the factor of "flat, not-sticky, moist, soft, and warm," which seems reasonable for leathers. Nonetheless, its semantic validity should be thoroughly investigated in the future.

IV. Discussion

It is noteworthy that the "luxury" and "comfort" factors are very similar as in Table 3. In the previous survey, when the

Table 3. Loadings of three factors for the perceptual layer. Left column lists the eight types of perceptual items in questionnaire.

	-Rough/Bumpy +Smooth/Flat(FY1)	-Soft/Warm +Hard/Cold(FY2)	-Resilient +Flexible(FY3)
-Soft +Hard	0.05	0.83	0.24
-Warm +Cold	-0.04	0.79	0.02
-Resilient +Flexible	0.16	0.22	0.99
-Smooth +Rough	-0.84	-0.03	-0.02
-Bumpy +Flat	0.75	-0.31	0.01
-Scratchy +NotScratchy	0.89	0.11	0.11
-With +W/O Tension	-0.34	-0.40	0.25
-Moist +Dry	-0.39	0.52	-0.06

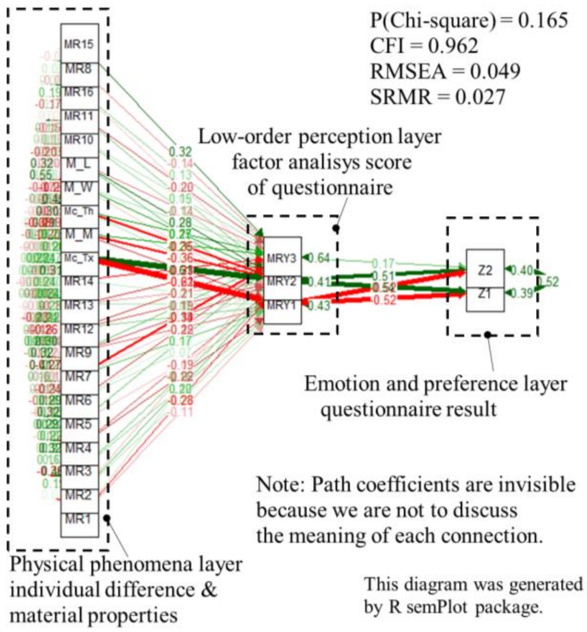

Fig. 3 Preliminary SEM path diagram

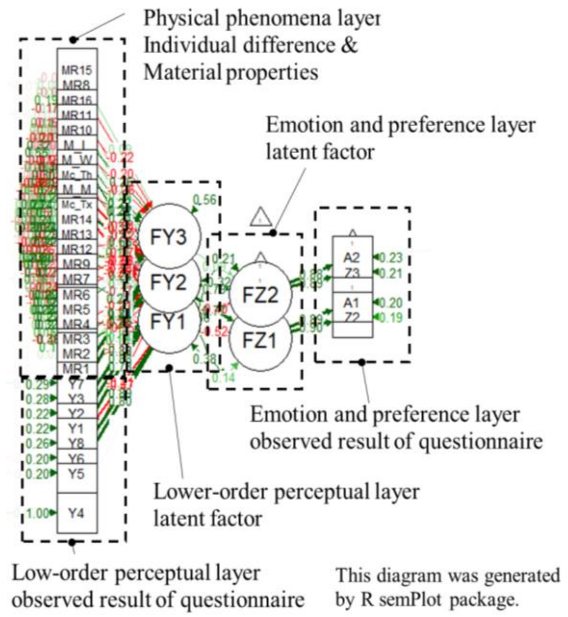

Fig. 4 Path diagram of Bayesian SEM

same questionnaire was given to in-house Japanese panelists and to European local base panelists, the Japanese panelists preferred only the comfort factor, while European panelists tended to prefer both the luxury and comfort factors. It is interesting that Japanese leather professional panelists exhibited the same evaluation tendency as the European panelists. This suggests that narrowing down the data based on user group or on location and age in future research, will make it possible to create an evaluation index close to market needs. In order to realize the evaluation index, it is necessary to collect data from various panelists in the future. Once evaluation indexes tailored to a wide variety of users are created from the collected data, the next step will be to classify the tendencies in end users' subjective responses and preferences, and build technology to predict them. This is likely to contribute to further improving the value associated with emotional and preferential responses.

V. Conclusion

Incorporating not only the physical property data collected by commercial measurement instruments but also the contact phenomena produced by the individual panelists as exogenous variables allowed us to model the causal relationship between perceptual responses, individual hand states, and touch behaviors. Bayesian SEM enabled hierarchical modeling that accounts for large repetitive errors that cannot be estimated using conventional SEM. As a result of incorporating the above two points, it has become possible to separate and model individual differences in physical phenomena and repetitive errors in answers to questionnaires.

Acknowledgment

We would like to thank all the people in the leather industry who participated in collecting data despite their busy schedules for their generous cooperation. We are fully committed to continuing to do our utmost to provide end users with the value defined by Quality of Time and Space.

Table 4. Regression model for FY1

+Rough/Bumpy/Scratchy -Smooth/Flat/NotScratchy (FY1)	Path coefficient
Normal force while sliding (MR1)	0.280
Shearing force while sliding (MR2)	-0.261
Magnitude of vibration above 50Hz (MR5)	0.322
Kurtosis of linear regression residuals of vibration spectrum (MR9)	0.238
Normal force while pushing (MR14)	0.283
Coefficient of friction while pushing (MR15)	-0.252

Table 5. Regression model for "luxury and comfort"

Emotion/Preference \ Perception	Path coefficient	
	+Cheap -Luxury (FZ1)	+Uncomfortable -Comfortable (FZ2)
+Rough/Bumpy/Scratchy -Smooth/Flat/NotScratchy (FY1)	0.525	0.404
+Hard/Cold/Dry -Soft/Warm/Moist (FY2)	0.769	0.788
+Flexible -Resilient (FY3)	-	0.090

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