Artificial tactile sensory system and high-precision AI simulation for cosmetic products

Lee, Jeong Yu[1,*], Jeong, Seong Min[1], Yi, Sungwon[1], Nam, Jin[1]

[1]Basic Research & Innovation Division, AMOREPACIFIC R&I Center, Gyeonggi-do, Republic of Korea

* Dr. J. Y. Lee, AMOREPACIFIC R&I Center, 1920 Yonggu-daero, Giheung-gu, Yongin-si, Gyeonggi-do, Republic of Korea, +82-31-899-2694, jeonglee@amorepacific.com

Abstract

Sensory evaluation is a critical step for the development of new products in the cosmetics industry. To date, this method relies on evaluations by professionally trained panelists. However, such approach is highly subjective and depends on the individual experience and skin sensitivities of the panelists. In this study, we introduced a novel artificial sensory evaluation system, named Sensonoid™, that mimics human behavior. Sensonoid™ was implemented to facilitate the digital sensory evaluation by measuring different variables, including spreadability, coolness, and adhesiveness. The system enables users to generate objectively reproducible sensory evaluation data with high correlation to the actual data obtained by human evaluation. In addition, an algorithm was developed to predict the sensory experience based on the ingredients of cosmetic products, achieving an accuracy of over 90% for the prediction of adhesiveness and spreadability. Furthermore, a simulation program based on artificial intelligence was established to predict the formulation or sensory experience using the data generated by the system. This innovative system can realize artificial sensory experiences with time-saving and cost-effective results compared to conventional clinical experiments.

Keywords: Artificial sensory evaluation system, AI simulation, Skin-like materials, Digital transformation

Introduction.

Rapid progress in the field of advanced materials has revolutionized various industries, including healthcare, robotics, and human–computer interfaces. An area of particular interest is the development of materials that can mimic and augment human-like sensory capabilities, such as touch and thermal perception [1, 2]. Artificial sensory evaluation systems are an emerging technology designed to mimic the function of human sensory organs [3, 4]. These systems can acquire, process, and interpret information from the environment similar to actual human functions [5, 6]. Artificial sensory systems aim to improve the quality of life and the performance of humans by providing accurate information on the environment.

The cosmetic and textile industry is a sector that relies on perceptual learning and experience with the sense of touch with the aid of professionally trained panelists to quantify the physical characteristics of products [7, 8]. However, accurate and consistent quantification is difficult to achieve because of the subjectivity of sensory perception. Several cosmetic studies utilize rheological or tribological instrumentation to determine the properties of skincare products [9, 10]. Although rheometer data depict the physical properties of the products, these properties rapidly change upon application owing to the skin temperature and rubbing motions. Consequently, sensor and artificial intelligence (AI) technologies have rapidly progressed over the past decade to facilitate the digital transformations in the cosmetics industry.

In this study, we developed a system that can measure the tactile senses similar to that of human perception. This system can acquire, process, and interpret information on personal care products. We obtained quantitative sensory data for different attributes, such as spreadability, adhesiveness, and coolness, for more than 100 products. In addition, machine learning analysis can facilitate the accurate and reliable processing and recognition of sensory information from sensors. We developed a machine-learning-based AI model by connecting these data with human sensory and rheological data. The developed system can be used to create formulations for specific sensory experiences or to discover the correct ingredients through AI simulations.

Materials and Methods.

Preparation of skin-like substrates

Base composites were prepared by manually mixing polydimethylsiloxane (PDMS, Sylgard 184 Silicone Elastomer Kit, CA) and a curing agent at a weight ratio of 10:1. Subsequently, 20 % hexagonal boron nitride (hBN, Avention, South Korea) and 0.1 % hydroxyapatite (HA, Topscience, China) was added to the base PDMS composite by weight and stirred manually until the materials are completely combined. The prepared hBN/PDMS/HA mixtures were placed in a vacuum chamber for 10 min to remove air bubbles. This step was omitted from the preparation of the samples containing air. The prepared hBN/PDMS/HA composites were placed in a scratched rubber mold and cured at 40 °C for 8 h to obtain the final products. Scanning electron microscopy (SEM, Carl Zeiss, Germany) was used to investigate the surface morphologies of the PDMS samples.

Measurement of tactile sensory perception

The tribology of the cosmetic products was evaluated by measuring the change in surface friction using a linear reciprocating method with the developed tactile sensor. Each 50 μL samples was loaded and measured back and forth at a specified speed and distance. The experiments were repeated in triplicate. All data are presented as mean ± standard deviation.

Measurement of thermal sensory perception

The sensor temperature was 32 ± 0.2 °C for the measurement. A 10 μm thick mesh was placed on the sensor plate, and 150 μL sample was applied. The temperature change was measured continuously for 200 s with a sensitivity in the range of milliseconds. Glycerine, propanediol, and butylene glycol (Sigma-Aldrich, St. Louis, MO, USA) were used as thermal stimuli. Each sample was mixed in a weight ratio based on water.

Machine learning-based prediction model

We used a deep-learning-based fully connected neural network to predict the cooling index for specific ingredient combinations. The coolness was predicted by randomly selecting the training and test data from the polyol combination measurement data with 45 and 3 samples, respectively, and analyzed 30 times. Adhesiveness and spreadability data were analyzed for the formulations of 81 products with 43 ingredients specified as variables. More than 1500 data points were obtained using data augmentation techniques. An adhesiveness test was performed on 22 random data samples with five replicates, resulting in 110 scatter points. The spreadability test data were based on 60 random samples with three replicates and 180 scatter points.

Results.

We previously developed artificial thermosensation equipment for the accurate and rapid measurement of the thermal sensation of skincare products [7]. In addition, we developed a spreadability evaluation device that can continuously measure the horizontal friction force to reflect human motion, which was customized to measure stickiness using vertical force. Sensonoid™ is a system that measures, analyzes, and simulates the data generated by these sensing devices (**Figure 1a**). A standardized methodology was established to ensure that at least 90% of the data for each device correlated with human ratings. This system and the conventional property measurement equipment can be used to collect multifaceted digital sensory data from a product. The digital sensory measurement system is highly reproducible and requires short measurement times compared to human evaluations, thereby obtaining large datasets. A perceptron-based multilayer neural network was introduced to complement the digital sensory evaluation system (Figure 1c). It specializes in learning sensory attributes, obtaining highly accurate predictions with the accuracy rate of more than 90% for tactile user sensations tailored to specific ingredient combinations. Consequently, our system can predict the final tactile sensation using ingredients and their proportions into the product as inputs. This technology can help researchers predict the tactile sensations of products based on their formulations and conversely, recommend formulations using the targeted sensory experience as the input.

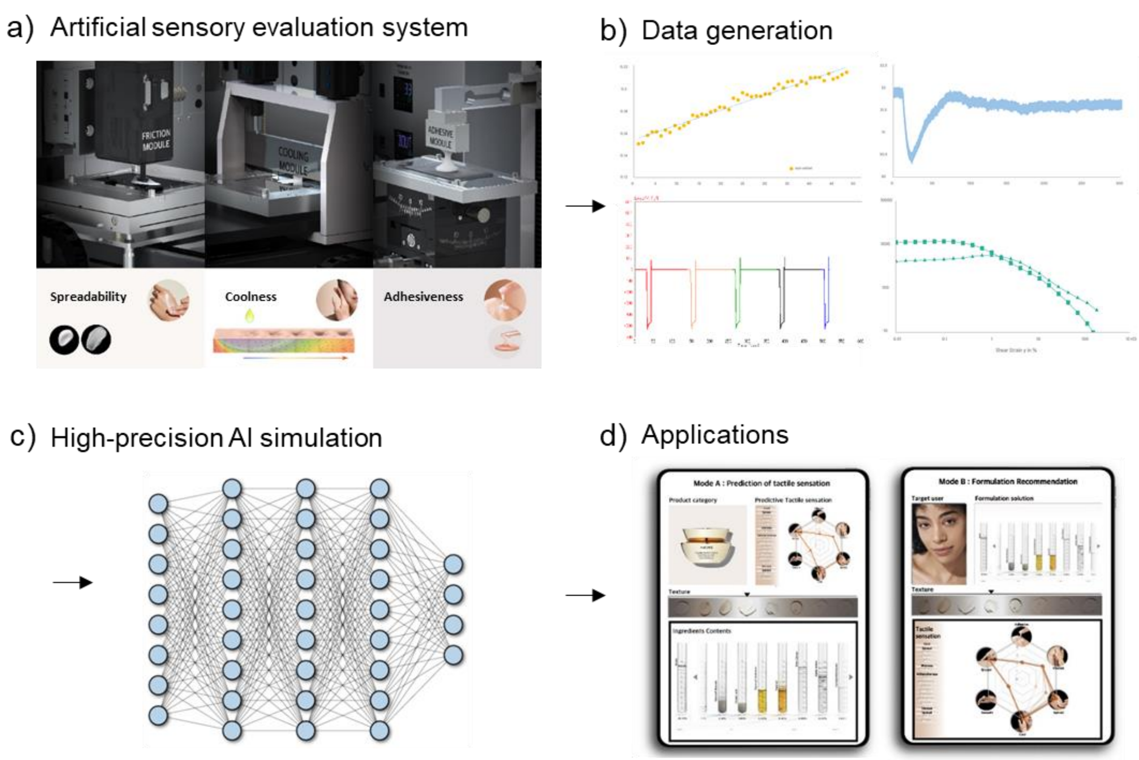

Figure 1. Flowchart of the Sensonoid system. a) Images of the developed sensory evaluation instruments. b) Data collected from the sensory artificial evaluation system. c) High-precision AI simulation with generated data. d) Developed applications to predict formulation or tactile sense.

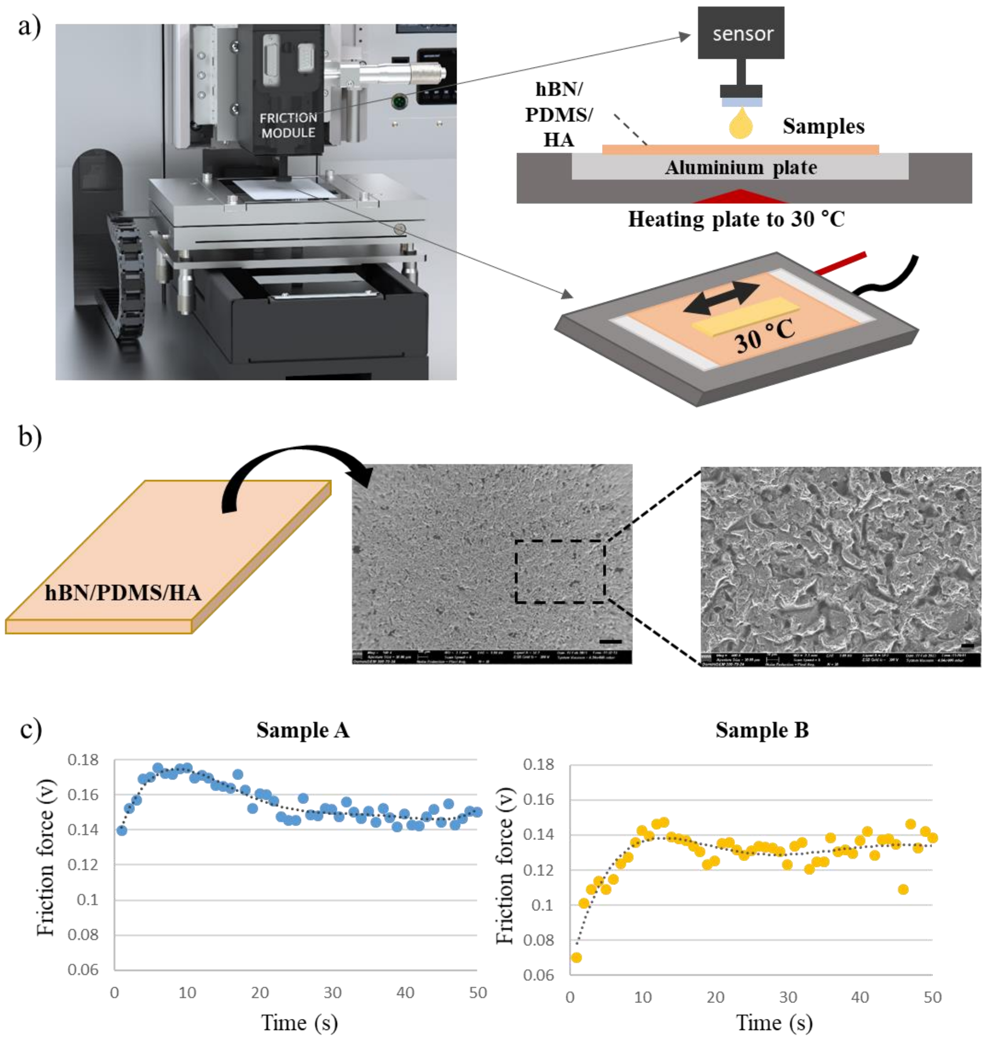

Figure 2. a) Image and schematic of the spreadability measurement device. b) SEM images of the upper surface of skin-like materials embedded in the plate. The scale bars indicate 500 μm and 50 μm, respectively. c) Data generated by the device. Continuous changes in friction force are measured to determine the tactile sensory experience of application.

Human skin translates environmental stimuli into electrical signals through sensory receptors to perceive tactile stimuli [7, 11]. Mechanoreceptors recognize static and dynamic mechanical stimuli, and the changes in surface friction when applying cosmetics can be considered a dynamic mechanical stimulus that indicates a sense of use [12]. The spreadability of the cosmetic products was measured using a piezosensor to measure the horizontal force and a load cell to measure the vertical force. We can continuously measure the change in the friction force by moving the product as if pressing it with a finger by applying a constant force to the sample (**Figure 2a**). The plate on which the sample is applied was maintained at 30 °C, which is similar to the skin temperature. A skin-like elasticity was achieved in the application plate by developing a PDMS-based skin mimetic (Figure 2b). Hyaluronic acid was introduced to provide skin-like elasticity, and hBN was added to compensate for the low thermal conductivity of PDMS. Skin-like softness and microflexibility were achieved by curing PDMS using scratch molding. Microcracks were observed on the surface using SEM. These surfaces increased the correlation with human data in actual experiments. Figure 2c shows the data generated by the device. Samples A and B are skincare products that are currently under development. The initial spreadability of the two products and friction changes as they were continuously rubbed can be visually compared using the proposed system.

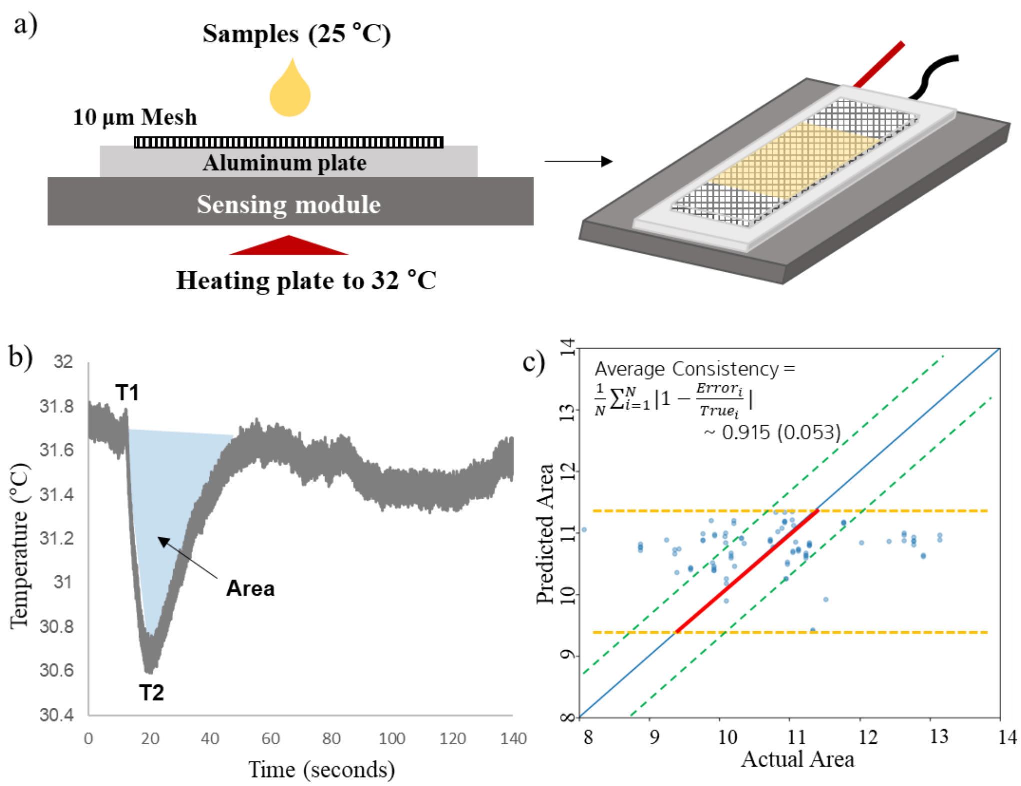

Figure 3. a) Schematic of the coolness measurement module on a heating plate at 32 °C and b) temperature changes. c) Comparison between the coolness data of the polymer combinations and prediction scores evaluated by the machine-learning algorithm.

Table 1. Combination of glycerin, propanediol and butylene glycol in water and analysis of coolness data measured with Sensonoid™.

#	Glycerin	Propane-diol	Butylene Glycol	Data		#	Glycerin	Propane-diol	Butylene Glycol	Data	
				T1-T2	Area					T1-T2	Area
1	20	0	0	1.08	12.94	24	3.75	0	11.25	0.88	9.77
2	0	20	0	0.96	12.02	25	0	7.5	7.5	0.90	10.85
3	0	0	20	1.13	14.50	26	0	3.75	11.25	0.91	10.54
4	15	5	0	0.95	11.11	27	0	11.25	3.75	0.85	10
5	10	10	0	0.98	11.76	28	7.5	3.75	3.75	0.84	9.81
6	5	15	0	1.01	13.19	29	3.75	3.75	7.5	0.84	9.52
7	15	0	5	0.96	11.11	30	3.75	7.5	3.75	0.88	9.73
8	10	0	10	0.86	9.38	31	10	0	0	1.19	16.68
9	5	0	15	0.94	9.26	32	0	10	0	0.92	12.66
10	0	10	10	0.93	9.73	33	0	0	10	0.99	10.95
11	0	5	15	0.87	9.99	34	7.5	2.5	0	1.02	15.30
12	0	15	5	0.88	10.04	35	5	5	0	1.02	12.90
13	10	5	5	0.79	9.89	36	2.5	7.5	0	1.06	14.04
14	5	5	10	0.85	10.24	37	7.5	0	2.5	1.02	11.28
15	5	10	5	0.90	10.12	38	5	0	5	0.91	11.26
16	15	0	0	1.16	13.11	39	2.5	0	7.5	0.90	9.88
17	0	15	0	1.04	14.41	40	0	5	5	0.93	9.73
18	0	0	15	0.96	11.68	41	0	2.5	7.5	0.87	9.99
19	11.25	3.75	0	0.97	11.15	42	0	7.5	2.5	0.90	10.41
20	7.5	7.5	0	0.99	11.04	43	5	2.5	2.5	0.88	9.73
21	3.75	11.25	0	0.96	11.01	44	2.5	2.5	5	0.79	9.21
22	11.25	0	3.75	1.00	10.38	45	2.5	5	2.5	0.76	8.97
23	7.5	0	7.5	0.89	10.79						

Thermosensation of different ingredient combinations was used to determine the effective formulation that can control skin temperature using the equipment (**Figure 3**). First, the thermal sensations of three types of polyols were evaluated, as shown in **Table 1**. The data were obtained every millisecond and drawn as a continuous graph (Figure 3b). An analysis program was developed for the quantitative analysis of the graphical data. The difference between the initial and lowest temperatures (T1-T2) and holding times are important factors of the cooling effect. Therefore, the integral values of the time and temperature differences were calculated and used as machine learning data. Further, a thermal prediction model with an accuracy of 91.5% was developed (Figure 3c).

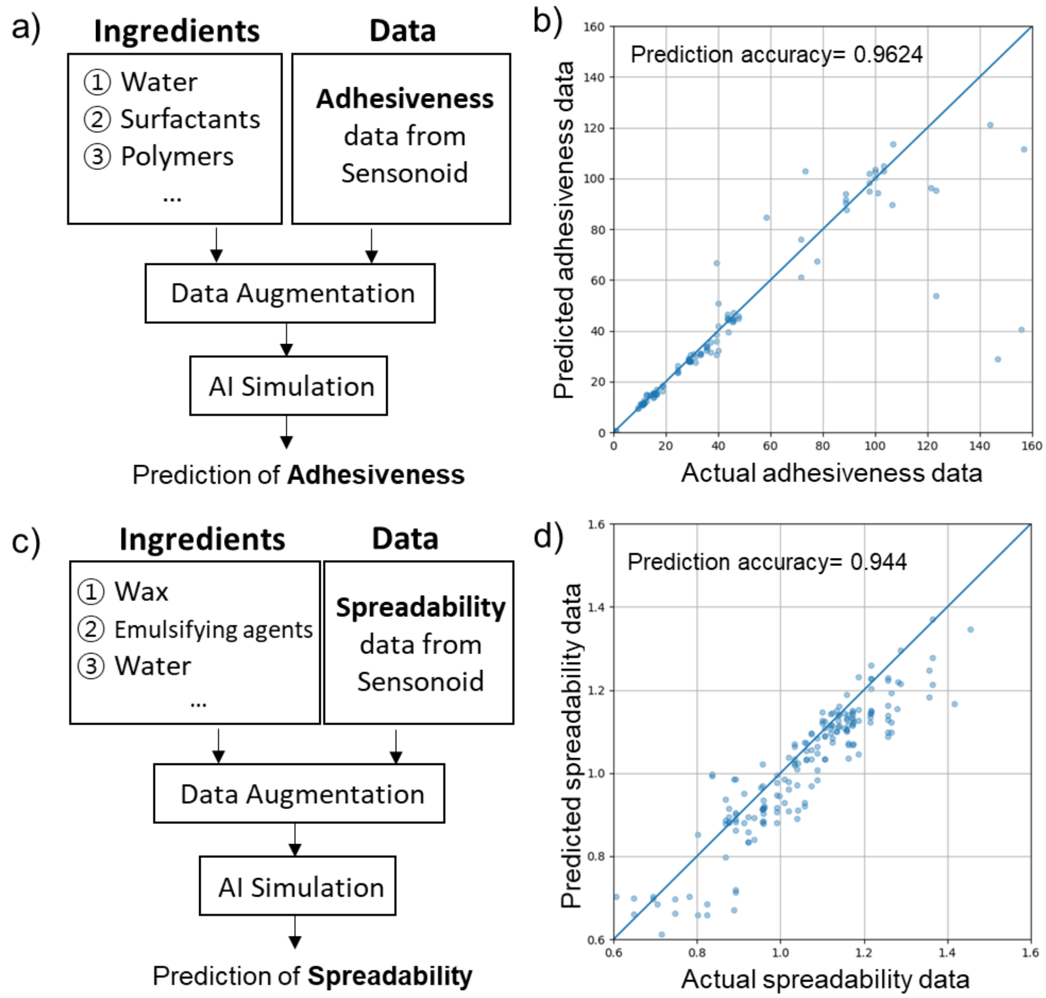

Figure 4. a) Framework for the prediction of adhesiveness with the generated data. b) Comparison of the predicted and actual adhesiveness data. c) Framework for the prediction of spreadability with the generated data. d) Comparison of the predicted and actual spreadability data.

Figure 4 shows the results of using data augmentation techniques and artificial neural network to predict the sensory experience of Sensonoid^{TM}. The predictive performance of artificial neural networks requires a large amount of data as the complexity of the given data increases and insufficient measurement data for cosmetic products consisting of various ingredient combinations poses difficulty. Data augmentation techniques were applied to improve the predictive power of complex ingredient formulation ratios by adding local structural information between arbitrary and similar datasets. For example, if there are N similar sensory data within a cutoff value around the i-th data point, the difference in the ingredient content between them is added to the existing data to train an artificial neural network to locally understand the sensory changes due to content variations. We designed a dual structure based on a fully connected layer to effectively determine the effects of usability on local variation information in the augmented data. Consequently, we predicted the sensory properties of a given ingredient formulation with high accuracy. The sensory attributes predicted by the AI model matched the adhesiveness and spreadability data detected by Sensonoid™ with high accuracies of 96.2% and 94.4%, respectively (Figure 4d).

Discussion.

This study explored the digital transformation of sensory assessments by combining tactile sensors and AI technologies. The rapid development of sensor technology and AI over the past decade has accelerated the pace of this digital transformation [13]. Although human assessment data are still the most meaningful and accurate information available, AI is becoming a tool that can compensate for the limitations of previously developed sensors [14]. In this study, we developed a device to measure tactile sensations that mimics human behavior when applying cosmetics.

We attempted to develop a reproducible system that would require less time and cost. Standardized measurement methods were established to ensure that the data obtained by the devices were highly correlated with the data evaluated by humans. In particular, we first focused on ensuring the reliability of the data and subsequently, generated the data. We measured products from different categories, including skincare, makeup, and body care products, and tested them under various conditions. In addition, product characteristics were recorded using conventional and widely used rheometer measurements. Relevant data of various attributes, including spreadability, stickiness, cooling, adhesion, and viscosity, were continuously collected. Based on the collected data, we used data augmentation techniques to create a sufficiently large dataset to create an artificial neural network simulation program for sensory predictions. Moreover, we investigated the effects of ingredients on the tactile sense of products and randomly prepared samples. Therefore, the simulation program demonstrated scalability for various elements in the cosmetics development phase. Thus, it can be used to identify alternative ingredients with the same sensory number or to demonstrate the expected change in the tactile sense as a result of changing ingredients, especially with the increasing need for ecofriendly ingredients. This approach saves time, money, and resources required to create new samples, facilitating a more environmentally friendly product development. As the cosmetics industry further discusses and explores these digital transformation technologies, we can expect to induce positive changes sooner.

Conclusion.

We developed digital sensory evaluation system which revolutionizes personal care by objectively measuring tactile sensations through high-precision AI simulations. By utilizing the developed system, it is possible to dramatically reduce the time and costs required compared to the conventional methods for product development and to predict sensory experiences. Using this system, we can quantify the differences in application, adhesiveness, coolness, etc. between products. Skin-like PDMS composites also hold great potential for artificial sensory evaluation, providing a means to accurately simulate human sensory experience and generate data on tactile perception. In conclusion, using this system, we not only get consistent answers for the same product, but we can also predict the exact sensation of use based on the product's formulations. In the next research, it is expected to be extended to enable fast learning models for various sensory evaluation. Furthermore, model refinement can be used to create formulation for specific sensory experience or to discover proper ingredients by AI simulation.

Acknowledgments.

This research was supported and funded by the AMOREPACIFIC.

Conflict of Interest Statement.

The authors declare no competing interests.

References.

1. Sun Z, Zhu M, Shan X, Lee C (2022) Augmented tactile-perception and haptic-feedback rings as human-machine interfaces aiming for immersive interactions, Nat Commun 13(1):5224.
2. Ge J, Wang X, Drack M, et al (2019) A bimodal soft electronic skin for tactile and touchless interaction in real time, Nat Commun 10(1):4405.
3. Wang J, Wang C, Cai P, et al (2021) Artificial Sense Technology: Emulating and Extending Biological Senses, ACS Nano 15(12):18671-18678.
4. Wang M, Luo Y, Wang T, et al (2021) Artificial Skin Perception, Adv Mater 33(19):e2003014.
5. Wang J, Liu X, Li R, Y. Fan (2023) Biomimetic strategies and technologies for artificial tactile sensory systems, Trends Biotechnol 6:203.
6. Sun F, Lu Q, Feng S, Zhang T (2021) Flexible Artificial Sensory Systems Based on Neuromorphic Devices, ACS Nano 15(3):3875-3899.
7. Lee Y, Park J, Choe A, et al (2022) Flexible Pyroresistive Graphene Composites for Artificial Thermosensation Differentiating Materials and Solvent Types, ACS Nano 16(1):1208-1219.
8. Guest S, McGlone F, Hopkinson A, et al (2013) Perceptual and Sensory-Functional Consequences of Skin Care Products, Journal of Cosmetics, Dermatological Sciences and Applications 13:3891.
9. Davies A, Amin S (2020) Rheology of Cosmetic Products: Surfactant Mesophases, Foams and Emulsions, J Cosmet Sci 71(6):481-496.

10. Nakano K, Kobayashi K, Nakao K, et al (2013) Tribological method to objectify similarity of vague tactile sensations experienced during application of liquid cosmetic foundations, Tribology International 63:8-13.

11. Lumpkin EA, Caterina MJ (2007) Mechanisms of sensory transduction in the skin, Nature 445(7130):858-65.

12. Johansson RS, Flanagan JR (2009) Coding and use of tactile signals from the fingertips in object manipulation tasks, Nat Rev Neurosci 10(5) (2009) 345-59.

13. Zhang Z, Wang L, Chengkuo Lee (2023) Recent Advances in Artificial Intelligence Sensors, Advanced Sensor Research 2(8):2200072.

14. Campo R, Carvalho FR, Rosato P, et al (2024) Sensory interactions in digital and virtual realities: new frontiers for the user experience, Frontiers in Communication 9:1.