Title:
Exploration of Product Aesthetics Based on Upper-Approximation of Rough Set Theory and Image Generative AI

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Introduction:
As science and technology continue to mature, differentiating products based on performance, functional features, or price becomes increasingly challenging. Consequently, companies must distinguish their products by focusing on subjective and abstract qualities such as aesthetics and comfort, which are assessed based on customers' feelings. In Japanese, this concept is referred to as "Kansei." The qualities evaluated by customer Kansei are known as "Kansei quality."

In the field of Kansei engineering (referred to as affective or emotional engineering), the methods for measuring customer Kansei or the impression of products have been developed and applied to many case studies. In these methods, semantic differential (SD) method [9] is widely used. Based on the measurement and analysis methods of customer Kansei, various aesthetic design methods have also been developed. These methods generate a new aesthetic design that a customer prefers best by revealing the relationships between the results of customers' Kansei evaluation of the same type of existing products as the design target and their aesthetic features. In these methods, various analysis methods such as artificial neural network [2],[3], rough set theory [4],[8],[11], GAN (Generative Adversarial Network) [1],[5],[9], Image generative AI [6],[7], etc. are used.

In Kansei engineering, rough set theory is frequently employed to analyze the correspondence between customer preferences and product aesthetics. In rough set theory, the relationship between decision attributes and condition attributes is represented by decision rules. When applied to Kansei engineering, customer preferences are typically treated as decision attributes, while product aesthetics are treated as condition attributes. There are two approaches to deriving decision rules in rough set theory, known as the upper and lower approximations. The upper approximation represents a set of objects that possibly belong to a target concept, allowing a certain degree of ambiguity, whereas the lower approximation represents a set of objects that certainly belong to the target concept and thus provides more reliable decision rules. In most studies applying rough set theory to Kansei engineering, including the authors' previous work, the lower approximation has been predominantly used. In contrast, this study attempts to utilize the upper approximation. The lower approximation does not allow the existence of objects that contradict a given decision rule, whereas the upper approximation allows the existence of such objects. As a result, the use of the lower approximation yields highly reliable decision rules, whereas the use of the upper approximation enables the extraction of a larger number of diverse decision rules. Therefore, when generating diverse product aesthetics to explore customer preferences, it is more appropriate to emphasize possibility rather than certainty.

In recent years, image generative AI has attracted increasing attention in Kansei engineering. Such techniques are commonly implemented using diffusion-based models, which can generate images from natural language text inputs, referred to as prompts. Decision rules extracted by rough set theory, which represent product aesthetics preferred by customers, are expressed in natural language.

For example, in the case of seating furniture, such decision rules are described using attributes such as type: office chair, backrest: mesh, and seat: fabric cushion. As a result, customers are required to imagine the corresponding concrete product aesthetics from these descriptions, which is less intuitive. In this study, product images are generated from decision rules using image generative AI, thereby facilitating Kansei evaluation of product aesthetics by customers.

Proposed Method:

In this study, a method is developed that combines the upper approximation of rough set theory with image generative AI to extract the relationships between customer preferences and product aesthetics in the form of decision rules, and to generate product images from these decision rules for broad exploration of product aesthetics aligned with customer preferences. The proposed method consists of the following three steps:

Step 1: Questionnaire Survey

Step 2: Analysis of Customer Preferences Using Rough Set Theory

Step 3: Generation of Product Aesthetics Using Image Generative AI

Step 1: Questionnaire Survey

First, a questionnaire survey is conducted to collect customers' preference evaluations regarding existing products.

Step 2: Analysis of Customer Preferences Using Rough Set Theory

Next, customer preferences are analyzed using rough set theory. First, the aesthetics of existing products used in the questionnaire survey are decomposed into a set of design attributes. For example, in the case of seating furniture, these attributes include type, backrest, seat, and legs, among others, which are treated as condition attributes. For each product, the design attributes that constitute the product are then identified and treated as the attribute values of the condition attributes. For example, a product can be described as type: sofa, backrest: leather, and seat: leather. Customer preference evaluations for each product are treated as decision attributes, and rough set analysis based on the upper approximation is conducted to extract decision rules associated with the preference "like."

Next, the covering index (CI) is calculated for each extracted decision rule. Finally, column scores of attribute values are calculated from the decision rules and their CI values. The column score indicates the degree to which each attribute value contributes to the decision attribute and, in the proposed method, represents the strength of its association with customer preferences.

Step 3: Generation of Product Aesthetics Using Image Generative AI

Finally, product aesthetics are generated using image generative AI based on text prompts. Prompts are constructed using the following two approaches:

- Column-score-based approach

For each design attribute, the attribute value with the highest column score is selected and included in the prompt.

- CI-based approach

The decision rule with the highest CI value is selected, and attribute values for design attributes not included in the selected rule are determined either randomly or by combining multiple high-CI decision rules without contradiction. The resulting attribute values for all design attributes are then incorporated into the prompt.

Case study:

To verify the effectiveness of the proposed method, it was applied to nine male students from Toyota Technological Institute. All participants provided informed consent prior to participation, and the study was conducted in accordance with institutional ethical guidelines. The design target was seating furniture. Since preferences for seating furniture vary across individuals, questionnaire results were analyzed separately for each participant, and product images were generated on a per-participant basis.

Step 1: Questionnaire Survey

First, approximately 3,000 images of seating furniture with a left-front view were collected from the Internet, and their backgrounds were removed. To ensure diversity in the questionnaire, image clustering based on visual similarity was performed, and the images were classified into 11 clusters. Fifteen images were then selected from each cluster, resulting in a total of 165 images used in the questionnaire. The survey was conducted online using Google Forms. An example of the questionnaire sheet is shown in Fig. 1.

Fig. 1: An example of a questionnaire sheet (好き: like, 嫌い: Dislike).

Step 2: Analysis of Customer Preferences Using Rough Set Theory

Next, decision rules were extracted using rough set analysis, where the design attributes constituting the seating furniture were treated as condition attributes and preference evaluations (like/dislike) were treated as decision attributes. For comparison, decision rules were derived using both the upper and lower approximations. Tab. 2 summarizes the highest-ranked decision rules obtained by the upper and lower approximations for each participant, and Fig. 2 illustrates the proportion of upper- and lower-approximation decision rules among the top 100 rules. These results indicate that the upper approximation yields substantially more decision rules than the lower approximation and that the CI values of upper-approximation decision rules are generally higher. Based on the extracted upper-approximation decision rules, column scores were calculated for each attribute value. Tab. 3 presents a subset of the column scores for Participant 1.

	Upper approximation			Lower approximation		
Subject	Best CI rank	Like	Dislike	Best CI rank	Like	Dislike
1	1	13	38	15	3	0
2	1	16	14	42	4	0
3	1	19	9	14	7	0
4	1	18	27	96	3	0
5	1	10	7	9	4	0
6	1	9	4	15	5	0
7	1	29	22	105	5	0
8	1	10	15	14	3	0
9	1	12	8	99	3	0

Tab. 2: Highest-ranked decision rules extracted by the upper and lower approximations and the numbers of seating furniture evaluated as “like” and “dislike” that satisfy each rule for each subject.

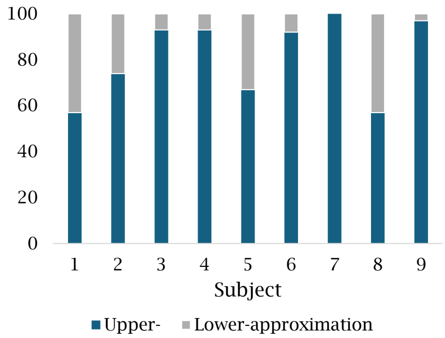

Fig. 2: Upper- and lower-approximation decision rules among the top 100 rules.

Type	Score
Armchair	3.66
Dining chair	1.65
Office chair	1.47

Armrest	Score
None	3.89
Wood	1.8
Fabric	1.53

Backrest	Score
Plastic	2.43
Fabric	2.41
Leather	1.78

Seat	Score
Leather	2.69
Plastic	2.39
Fabric	2.34

Tab. 3: Examples of column scores for design attribute values for Subject 1.

Step 3: Generation of Product Aesthetics Using Image Generative AI

In the case study, product aesthetics were generated using Stable Diffusion v1.5 [10]. Using the column-score-based approach, ten images of seating furniture were generated by constructing prompts that included, for each design attribute, the attribute value with the highest column score. Using the CI-based approach, ten images were generated by determining attribute values from the decision rule with the highest CI value, while attribute values not included in the selected rule were determined randomly. For comparison, an additional twenty images were generated using fully random attribute values. Examples of the generated images are shown in Fig. 3. The total of forty generated images were then re-evaluated by the participants. Tab. 4 shows the proportion of images evaluated as "like." The results indicate that seating furniture generated based on CI values or column scores was preferred over randomly generated furniture. Although furniture generated using column scores was slightly more preferred than that generated using CI values, the difference was small. These results confirm that the proposed method can generate product aesthetics preferred by customers based on questionnaire results for existing seating furniture.

Fig. 3: Examples of generated product images.

Subject	Column-score-based	CI-based	Random
1	0.3	0.8	0.25
2	0.7	0.6	0.45
3	0.7	0.9	0.6
4	0.3	0.7	0.6
5	0.9	0.6	0.6
6	0.7	0.7	0.75
7	0	1	0.5
8	0.5	0.4	0.4
9	0.9	0.5	0.45

Tab. 4: Proportion of generated product images evaluated as “like” by subjects.

Conclusion:

This study proposed a method that integrates rough set theory based on the upper approximation with image generative AI for exploring product aesthetics aligned with customer preferences. By extracting possibility-oriented decision rules, the proposed method enables broad capture of customer preferences, and by visualizing these rules as product images, it facilitates intuitive Kansei evaluation of product aesthetics. A case study on seating furniture suggests that the proposed approach is effective for generating product aesthetics preferred by customers.

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References:

[1] Dai, Y., Li, Y., Liu, L.: New Product Design with Automatic Scheme Generation, Sensing and Imaging, 20(29), 2019. http://dx.doi.org/10.1007/s11220-019-0248-9
[2] Hsiao, S.W.; Huang, H.C.: A neural network-based approach for product form design, Design Studies, 23(1), 2002, 67-84. http://dx.doi.org/10.1016/S0142-694X(01)00015-1
[3] Kobayashi, M.; Kinumura, T.; Higashi, M.: A Method for Supporting Aesthetic Design Based on the Analysis of the Relationships Between Customer Kansei and Aesthetic Element, Computer-Aided Design & Applications, 13(3), 2015, 281-288. http://dx.doi.org/10.1080/16864360.2015.1114385
[4] Kobayashi, M., Niwa, K.: Method for Grouping of Customers and Aesthetic Design Based on Rough set theory, Computer-Aided Design & Applications, 15(4), 2018, 565-574. http://dx.doi.org/10.1080/16864360.2017.1419644
[5] Kobayashi, M.; Thongpramoon, P.: Generation of Product Design Using Gan Based on Customer's Kansei Evaluation, 9th International Conference on Kansei Engineering and Emotion Research 2022, Barcelona, Spain, September 6-9, 2022. https://dx.doi.org/10.5821/conference-9788419184849.35
[6] Kobayashi, M.; Kume, K.: Design Generation Using Stable Diffusion and Questionnaire Survey, Computer-Aided Design & Applications, 21(5), 2024, 859-868. https://dx.doi.org/10.14733/cadaps.2024.859-868
[7] Li, B.; Hu, Z.; Liu, Y.; Wang, Z.: Integrating Kansei Engineering and AI-Generated Image for Commercial Vehicle Body Morphology Design. Symmetry, 17(11), 2025, 1971. https://doi.org/10.3390/sym17111971
[8] Ohki, M.; Harada, T.; Inuiguchi, M.: Decision Rule Visualization System for Knowledge Discovery by Means of the Rough Set Approach, Journal of Japan Society for Fuzzy Theory and Intelligent Informatics, 24(2), 2012, 660-670. http://doi.org/10.3156/jsoft.24.660
[9] Schmitt, P. Weiss, S.: The Chair Project, https://philippschmitt.com/work/chair.
[10] Stable diffusion, https://github.com/CompVis/stable-diffusion, CompVis.

[11] Yamada, K.; Moroga, U.; Unehara, M.: Design Support for Generating Novelty with Rough Sets Theory and Conceptual Hierarchy, Transactions of Japan Society of Kansei Engineering, 11(1), 2012, 17-26. http://dx.doi.org/10.5057/jjske.11.17