1. INTRODUCTION

In this study, the authors focus on the ambiguous and malleable nature of Kansei decision-making criteria and propose a method for the analysis and modeling of the characteristics of the Kansei decision-making process.

Decision making involves the process of deciding on a wide range of choices according to one’s own criteria. People are forced to make various decisions in their lives. In today’s society, where quick decision making is required amid a vast volume of information, effective support methods for decision making are essential. Previous studies on decision making have assumed that decision makers have clear goals and judgment criteria and that rational decisions are made according to these goals and criteria.

However, in actual decision making, judgment criteria often change dynamically, depending on the situation and context, and people are required to make decisions based on their own Kansei. Real-world decision-making problems often do not have a single fixed answer. Such a problem is called a “ill structured problem,” and it is difficult to solve it with a computer. However, human beings are able to make decisions in a compromised manner. Especially in the case of Kansei content, people tend to make decisions based on their own Kansei. Kansei includes not only preferences and values but also mood and context. Kansei is arguably a dynamic phenomenon. Some people are clear about what they want, while others are not. If it is unclear what they want, they are likely to be influenced by the selection process. It is a meaningful task for Kansei engineering to investigate in detail and analyze mathematically the nature of the influence of the selection process.

In this experiment, we employed the decision tree to propose a method for modeling the structure of Kansei decision-making processes. The use of the decision tree to represent Kansei decision-making processes and compare the structures of various decision trees that reflect the Kansei of decision makers allowed us to extract and quantitatively evaluate the factors that influence the structures. Next, to gather examples of decision making, the authors conducted a simulated experiment. This is a choice experiment that assumes the purchase of a product. In this case, the authors investigated how the selected products changed when the conditions repeatedly changed for several people. The authors then applied the decision tree modeling method to the experimental results. The resulting decision trees are expected to reflect the different Kansei of different people and cases. Finally, we examined how decision trees differ depending on the presence or absence of attachment to a product and, subsequently, confirmed that differences in Kansei originate in differences in the structures of decision trees.

2. RELATED RESEARCH

Decision making is the process of choosing one or several alternatives from a collection of selectable alternatives. Many theoretical studies on decision making have been conducted in multiple disciplines, including sociology, psychology, business administration, and economics.
Considerable decision-making support research has been carried out in the field of engineering.

Studies on traditional decision-making models (e.g., Simon [1] and Sage [2]) assume that decision makers have clear goals, demands, and criteria and that rational decisions are made in accordance with the set goals and criteria. In addition, traditional research in engineering has relied on rational decision making, assuming that decision-making criteria are static. Saaty’s hierarchical analysis method (AHP) is often used to rationally determine solutions [3]. The AHP is a method to quantitatively measure the importance of evaluation criteria to show rationality and to guide decision making. In addition, it has been applied to many decision-making support systems [4]. Thus, conventional decision-making research has tried to explain the decision-making process, which is originally a bad structure problem, by reducing it to a good structure problem. Therefore, the impact of the interaction process is excluded, and it is assumed that decision-making criteria will not change according to the situation.

Several studies, including those in behavioral economics, have pointed out that people’s decision making is influenced by emotional factors. Mottelini points out that decision makers’ criteria are dynamically changing according to the situation and that actual decisions are made emotionally [5]. According to Kahneman and Tversky’s [6] prospect theory, various cognitive biases exist in human decision making. Decision making is well known to be nonlinear and situationally variable due to cognitive bias. Particularly in Kansei decision making, the utility of expectations cannot be objectively judged. It is difficult to determine decision-making criteria, and the influence of cognitive bias is said to be large and irrational [7]. However, these studies have been limited to behavioral observations and qualitative feature analysis, while feature analysis using an engineering approach receives limited attention.

As mentioned above, the method of supporting rational decision making involves supporting decision making based on “static criteria.” However, the actual decision-making process is considered to be dynamic and malleable according to the situation. Therefore, in this study, we propose an approach to the decision-making process that changes in tandem with the situation. In this study, the decision-making process is presented as a decision tree, and the shape of the tree reflects the Kansei of the decision maker, assuming that decision criteria change dynamically in Kansei decision making. The proposed method of this study can be used as a basis for modeling the Kansei decision-making process.

3. EXPERIMENTAL PROCEDURES

In this experiment, the authors assumed a decision-making process in which, based on several decision-making criteria, they narrowed down the candidates and finally chose one from a large number of choices. This kind of decision making is a common phenomenon in normal decision making (e.g., online shopping) and is considered to be useful as a setting. In their previous study, the authors experimented with a decision-making task using a clock as an example [8, 9].

The authors present the decision-making process as a decision tree. They will do so by considering the order of choices based on decision-making criteria as the path for the decision tree. A decision tree is an algorithm that performs classification by creating one rule after another, dividing the data [10]. The decision tree takes an attribute for the node and a value for the arc. A value can be a single value or a set of values, including intervals. The leaf (the bottom node) represents the choices, including multiple choices. When framed this way, one product of the selection process (i.e., the decision-making process) is presented as one decision tree.

The resulting decision trees vary from person to person and from condition to condition. Figure 1 shows the decision tree that illustrates a single product of the selection process. In other words, a person’s Kansei when a decision is made under certain conditions. Figure 1 displays the sequential selection process of three attributes of a given product and the selection of the most preferred product from the remaining products. Among all products, the products that fit the attribute selected in Attribute 1 are narrowed down, leaving behind the products that fit the attribute selected in Attribute 2. Furthermore, there are still products that match the attributes selected in Attribute 3.

![Figure 1: An image of decision tree](image-url)
and the process involves selecting one of the most preferred products from the final remaining products. It is also possible to merge the decision trees of a person choosing the same product in various conditions. This means that if the values of each attribute selected in Attributes 1, 2, and 3 are the same, the final remaining choices will be the same. Therefore, in this case, the authors will merge the selection processes assuming that they are the same.

The merged decision tree is presumed to reflect the differences in individual Kansei (e.g., fluctuations in product selection and degree of preference) in the product. The procedures for merging the decision trees and summarizing the nodes are described in detail in Chapter 5.

In ID3 (the most popular decision tree learning), a data set of input data and output pattern, the algorithm selects the attribute with the highest mutual information content, divides the data set according to that attribute, and constructs the if-then rule of the tree structure [11]. Because the concept of information quantity is employed, “uncertainty,” “ambiguity,” and “clutter” can be minimized, and the number of divisions required to create the decision tree can be reduced [12]. However, the ID3 cannot handle numeric attributes. As a result, a fuzzy ID3 is proposed that can handle numerical attributes by using a fuzzy set of attribute values [13].

Some studies have applied decision trees to Kansei data. Miyoshi et al. fused projective tracking and fuzzy ID3 to examine the relationship between product design elements and psychological quantities represented by Kansei words. They proposed a projection tracking ID3 to visually illustrate the relationship between design elements and psychological quantities [14]. Using the golf club as an example, Tokumaru et al. proposed a method to analyze the usability and attractiveness of a product using decision trees [15]. Using decision trees obtained from a bouquet’s Kansei data, Inoue et al. extracted valid rules and applied them to a bouquet presentation system [16]. Although many studies have used Kansei data to create decision tree models, very few studies have modeled Kansei decision-making processes with dynamic changes in decision-making criteria using decision trees. Therefore, this study is significant.

4. EXPERIMENTAL METHODS

The authors experimented with the conditions to unify them in the decision tree. The way the decision tree is presented is described in Chapter 3. Specifically, the authors conducted an experimental task to choose one watch from 200 watches [8, 9]. After three rounds of refinement, the participants selected the watch they liked the most from the final remaining watches. Since there were three conditions for refinement, there were six ways of doing so if the authors swapped the order. Therefore, the participants made six selections in total.

The authors also asked the participants whether they had a particular watch in mind, whether some patterns were the easiest to choose, or whether there was a watch that they liked the most among the watches they chose in the end. Twenty male participants (undergraduate and graduate students) took part in this experiment [Note 1]. The authors consider that it is important to understand each person’s Kansei as the structure of the decision tree, and the number of subjects is reasonable.

Some of the watches presented to the participants are shown in Table 1, and the combinations of the six different selection orders are shown in Table 2. The product list shows nine attributes of the watches: price, plate color, plate diameter, belt color, belt width, belt type (leather, metal, nylon, silicone), average monthly difference, and whether it is a limited-edition product or water resistant. The price is within the range that male college students can afford, and we selected watches that male college students could purchase.

| No | Brand      | Name                                | Design | Price  | Plate Color | Belt Color | Belt Type | Limited Item | Water-proof | Average Month Difference | Belt Width (cm) | Plate Diameter |
|----|------------|-------------------------------------|--------|--------|-------------|------------|-----------|--------------|-------------|--------------------------|----------------|---------------|
| 1  | Paul Smith | PS by Paul Smith Watch             |        | ¥27,000| Blue        | Blue       | 2         | 1            | 5           | 20                       | 1.8            | 3.4           |
| 2  | Paul Smith | PS by Paul Smith Watch             |        | ¥32,400| Black       | Black      | 2         | 1            | 5           | 20                       | 1.8            | 3.4           |
| 3  | Paul Smith | Closed Eyes Mens Watch             |        | ¥33,480| White       | Brown      | 2         | 0            | 10          | 20                       | 1.9            | 3.5           |
The authors hypothesized that if a person has decided what he or she wants (i.e., is particular about the item), he or she will choose the same thing (or a similar thing) all six times, and if the person is unclear about what he or she wants, the selection results will be different. After testing the hypotheses, some real variations emerged in the selection results (see Chapter 5 for details).

5. EXPERIMENTAL RESULTS

The authors investigated how the selection order of product attributes changed the outcome of product selection. The results showed that only one participant selected the same watch, while the remaining 19 participants selected different watches depending on the order of selection. The variations in the number of products selected varied among the participants. However, it was larger for the participants who answered "no" than for those who had a particular watch in mind (see [8, 9] for details).

In the experiment, the authors applied the decision tree modeling method described in Chapter 3 to the experimental results. As shown in Table 2, the order of selection of price, plate color, and belt color was swapped, and the participants were asked to make their choices in six different patterns. If the combination of the three attributes selected for price, plate color, and belt color is the same, albeit with a different order of selection, the final remaining watch choices are the same. Therefore, in this study, the same combination of the three attributes is considered to be the same and presented as a decision tree.

The decision tree in this study has the price as the first layer, the plate color as the second layer, and the belt color as the third layer, and the number of nodes is the same as the number of attribute types selected by the participants. For example, Table 3 shows the selection results of the participant who was particular about the watches (Participant 2), and Table 4 shows the selection results of the participant who was not particular about the watches (Participant 12). Looking at Table 3, the price range of all the patterns is ~15,000 yen, and the plate color is black. However, only Pattern B has a black belt, with the other patterns being silver. Since Patterns A, C, D, E, and F have the same combination of attributes and the final remaining watches are the same, they are considered to be on the same path as the decision tree. Therefore, only the decision tree for Participant 2 is shown in Figure 2. According to Figure 2, the selection of the watch is premised on a total of two patterns of paths: (a) the price range and the plate color, and (b) the belt. Next, according to Table 3, selection of price, plate color, and belt color were swapped, and the participants were asked to make their choices in six different patterns. If the combination of those three attributes selected for price, plate color, and belt color is the same, albeit with a different order of selection, the final remaining watch choices are the same. Therefore, in this study, the same combination of the three attributes is considered to be the same and presented as a single decision tree.

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the watches (Participant 12). Looking at Table 3, the
price range of all the patterns is ~15,000 yen, and the
plate color is black. However, only Pattern B has a black
belt, with the other patterns being silver. Because Patterns
A, C, D, E, and F have the same combination of attributes
and the final remaining watches are the same, they are
considered to be on the same path as the decision tree.
Therefore, only the decision tree for Participant 2 is
shown in Figure 2.

According to Figure 2, the selection of the watch is
premised on a total of two patterns of paths: (a) the price
range and the plate color, and (b) the belt. Next, according
to Table 4, only Patterns C and D have a price range
of ~40,000 yen, and the plate and belt colors are black.
Moreover, since the combination of attributes is the same,
they are considered to be the same path. Therefore, only
the decision tree for Participant 12 is shown in Figure 3.

Figure 2 shows that the selection of the watch is
premised on a total of five patterns of paths: price range,
three different plate colors, and two different belt colors.

The comparison of Figures 2 and 3 shows that the
participants who are not particular about the decision tree
structure tend to be more complex than those who are
particular about it.

6. DISCUSSION

6.1 Differences in characteristics vis-à-vis differences
in preoccupation

In this section, the authors compare and analyze
the differences in the decision-makers’ characteristics
according to the extent to which they are particular about
a product.

First, to examine the differences in the characteristics
of the decision trees, the number of nodes in the decision
trees was compared. Table 5 compares the number of
nodes for the determinants of attribute values and the
number of product choices according to whether the
participants were particular about the product. In Table 5,
“Y” indicates the number of nodes for each attribute
for the eight participants who answered “strongly,” and
“N” indicates the number of nodes for the 12 participants
who answered “not strongly.” The average number of
nodes for each attribute in Table 5 suggests that the group
that is particular about any attribute has fewer nodes on
the decision tree than the group that is not particular
about any attribute.

Next, to determine whether there are any differences in
attribute values and the number of product choices for
the groups with and without preferences, the authors
conducted the Mann–Whitney’s U test (Wilcoxon’s rank-
sum test). This is the test of differences in nonparametric
representative values. In this experiment, the one-tailed
test was used to determine whether there was a differ-
ence rather than a large or a small difference.

The p-values of the test results are shown in Table 6.
According to Table 6, the price range and the plate color
were found to have a significance level of 5%. Therefore,
the number of nodes on the decision tree for the price
range and the plate color was less for the participants
who were particular about the watches than for the
participants who were not.

Next, an analysis was performed using the features
attained in previous studies [8, 9]. To investigate the
similarity of the watches, the authors conducted a cluster
analysis of target products using Quantification III.
Quantification III is a method that aids in identifying a
small number of latent variables from a large number of
observed variables. In a previous study, Quantification III
was conducted using three attributes of watches (price,
Table 5: Comparison of the number of nodes by whether or not the participants are particular about the watches (product attributes and the number of the selected products)

| Price range | Plate color | Belt color | Watch selection |
|-------------|-------------|------------|-----------------|
| No.         | Y | N | Y | N | Y | N | Y | N |
| 1           | 2 | 3 | 2 | 1 | 2 | 3 | 3 |    |
| 2           | 1 | 2 | 3 | 1 | 2 | 1 | 3 | 4 |
| 3           | 1 | 2 | 1 | 3 | 2 | 2 | 2 | 3 |
| 4           | 1 | 2 | 2 | 1 | 2 | 2 | 1 | 3 |
| 5           | 1 | 1 | 2 | 3 | 2 | 1 | 2 | 3 |
| 6           | 1 | 6 | 2 | 5 | 4 | 6 | 6 |    |
| 7           | 3 | 3 | 3 | 3 | 2 | 2 | 4 | 3 |
| 8           | 1 | 2 | 2 | 1 | 1 | 1 | 2 | 2 |
| 9           | 2 | 2 | 2 | 3 | 4 |    |    |    |
| 10          | 1 | 3 | 3 | 3 | 5 |    |    |    |
| 11          | 1 | 3 | 3 | 2 | 4 |    |    |    |
| 12          | 1 | 2 | 2 | 2 | 4 |    |    |    |
| Ave         | 1.38| 2.25| 1.88| 2.67| 2.00| 2.08| 3.00| 3.75|

Table 6: Test results (product attributes and the number of the selected products)

| Price range | p-value (one-sided) |
|-------------|---------------------|
| Price range | 0.031 < 0.05        |
| Plate color | 0.026 < 0.05        |
| Belt color  | 0.399 > 0.05        |
| Watch selection | 0.077 > 0.05      |

Table 7: Comparison of the number of nodes by whether or not the participants are particular about the watches (total distance and the number of clusters)

| Total distance | The number of cluster |
|---------------|-----------------------|
| No.           | Y | N | Y | N |
| 1             | 2.59| 1.76| 2 |    |
| 2             | 0.88| 4.70| 1 | 2 |
| 3             | 0.99| 1.80| 1 | 1 |
| 4             | 0.00| 3.18| 1 | 2 |
| 5             | 2.05| 2.42| 2 | 1 |
| 6             | 13.49| 24.29| 2 | 3 |
| 7             | 16.27| 4.50| 2 | 3 |
| 8             | 1.17| 0.51| 2 | 1 |
| 9             | 11.38| 2    |    |    |
| 10            | 13.62| 2    |    |    |
| 11            | 6.69| 1    |    |    |
| 12            | 3.88| 1    |    |    |
| Ave           | 4.68| 6.56| 1.63| 1.83|

Table 8: Test results (total distance and the number of clusters)

| Total distance | p-value (one-sided) |
|---------------|---------------------|
| The number of cluster | 0.102 > 0.05 |

The number of clusters for the groups with and without preferences were any differences in total distance and number of clusters. Next, to determine whether there were any differences in total distance and number of clusters for the groups with and without preferences, the authors performed a cluster analysis using sample scores and classified the 200 watches into three clusters.

The authors determined the number of clusters of the final selected watches. The results comparing the total distance and the number of clusters with and without the participants’ tendency are shown in Table 7. According to the mean total distance and the mean number of clusters in Table 7, the participants who had a particular watch in mind had a longer total distance and a slightly higher number of clusters. Next, to determine whether there were any differences in total distance and number of clusters for the groups with and without preferences, the authors performed the Mann–Whitney’s U test (Wilcoxon’s rank-sum test), and this is the test of differences in nonparametric representations. The test results are shown in Table 8. According to Table 8, the results of the test were not significant.

The authors compared the analytic results of the number of decision tree nodes for each attribute of the commodity, and the number of commodity selections with the analysis results of the total distance and number of clusters. The number of decision tree nodes, the total distance, the number of clusters for each product attribute, and the number of product selections tend to be smaller for the participants who were particular about the products than for those who were not. However, only the price range and the plate color were significant. The reason why the tests for the total distance and the number of clusters were not significant is that all three attribute values were used to calculate the total distance and number of clusters. When the number of nodes in the decision tree was tested for each attribute, only the price range and the plate color were significant. This allows us to extract more specific features. The reason is because the participants were perhaps very particular about the price range and the plate color and that their judgment criteria did not change even when they had selected a specific plate multiple times.

In summary, the number of nodes in the decision tree was used in this experiment to quantitatively evaluate the irrationality of decision makers. In the future, the authors will compare the number of nodes, the number of leaves, the number of branches, and the depth of the hierarchy of various decision trees. They will also quantitatively evaluate the features that cause differences in the structure of decision trees. The authors will also extract the human-related elements that produce differences in the decision-making structure. This will make it possible to quantitatively determine the factors that influence judgment criteria in emotional decision making. This study contributed to the literature by proposing a method and showing its usefulness for decision making.
6.2 Similarities and differences vis-à-vis related studies

In this experiment, the authors applied the method proposed in Chapter 3 to the product selection experiment and visualized the differences in Kansei regarding the selection of a watch using the decision tree. Furthermore, using the number of nodes in the decision tree, the authors quantitatively showed the features that make a difference in the structure of the decision tree. The authors investigated how the selection results change depending on the selection order of the product attributes.

It was found that many participants had different selection criteria depending on the selection order. This is consistent with Mottelini’s arguments and the prospect theory discussed in Chapter 2. Mottelini [5] states that decision makers’ criteria are dynamically changing according to the situation.

Based on the prospect theory [6], decision making is nonlinear due to cognitive bias and varies according to the situation. This is particularly valid in Kansei decision making where cognitive bias precludes determining decision-making criteria. In this experiment, the change in the order of selection may have influenced the participants’ decision criteria and resulted in uneven selection results. The authors found that the participants who were not particular about the products had less difficulty in determining their judgment criteria than the participants who were particular about the products.

Although previous studies have examined the irrationality of decision makers, these studies have been confined to the observation of behaviors and the analysis of qualitative features. In this experiment, the engineering approach of decision tree analysis was used to visualize the variability of decision-making criteria and extract features that indicate the irrationality of decision makers.

Next, regarding the relationship between user attributes and commodity attributes, Nakajima et al. [17] assumed that the data structure of commodities interferes with many commodity choices, meaning that the user attributes define the commodity attributes. Maeda et al.’s [18] employment guidance and Sugimoto et al.’s [19] reading consultation system are examples that have examined the interference between user attributes and product attributes. The employment guidance system deals with the variations in the values of user attributes (e.g., place of origin and gender) given to product attributes, such as facilities and place of employment. The reading consultation system deals with the interference between a child who is the reader (age and gender) and the content, such as the characters and subject matter.

As mentioned above, previous studies’ results of fluctuations in value are consistent with the results of this study. However, the previous studies have discussed the attributes of decision makers, whereas this study focused on the presence or absence of attachment to the product. This is a feature that people may be particular about, even if not well aware of. In this study, the decision tree analysis was applied to the selection results, which helped in analyzing in detail the participants’ unconscious minds and what they were preoccupied with. In a previous study, the authors compared the gender differences in the variations of selection results and discovered that women tend to have more variations in their selection results than men. In this paper, the authors only presented the results affecting men. In the future, the authors will conduct similar analyses for other products and attributes, including age and gender.

7. CONCLUSION

In this study, the authors proposed a method to model the decision-making process using the decision tree. Next, a mock experiment was conducted to collect examples of decision making. The authors then applied the decision tree modeling method to the experimental results. The resulting decision trees allowed us to visually grasp the different Kansei of different people. Finally, the authors compared the differences in the number of nodes in the decision tree to determine the extent to which the participants were attached to the product. The results confirmed that the differences in Kansei were reflected in the different structures of the decision tree.

The fact that the proposed method allowed us to represent the decision-making process in decision trees renders it applicable to machine learning. The findings of this study can be drawn on to apply machine learning to emotional thought processes for learning and prediction in the future. Further, smart watches are becoming more popular in recent years, and it is necessary to experiment with various types of watches by increasing their attributes.

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NOTE
[Note 1] The research procedures followed the Code of Ethics for Human Research of the Faculty of Science and Engineering of Chuo University.
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