A study on the psychological change of consumer based on AIDAS model

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Abstract:
Many companies need to know how to appeal to consumers in favor of their products and services by broadcasting commercial messages (CMs) through TV. CMs are expected to create and nurture the best image of the company and the products among consumers, and to promote the purchasing activities of consumers through consumer viewing. However, these effects are difficult to produce without strategies. CMs should be designed with the appropriate concept and content. Therefore, there is a need to recognize what stimulates the psychological change in consumers leading to purchase activity: that is, the physical change of recognizing the item and buying the item. Subsequently, and the element(s) of the physical change should be analyzed to shed light on the appropriate target consumers for designing CMs.

In this study, we focus on a popular yogurt brand in Japan called “Meiji’s Purobio yogurt R-1”, analyzing the psychological change in consumers attributed to CMs on TV based on the attributes of 3,000 consumers’ data and their TV browsing history. For grasping the psychological state of consumers, we apply the attention, interest, desire, action, satisfaction model and define the consumers’ five psychological states based on questionnaire data. The factors of CMs with effects on consumers in each psychological state are clarified using two clustering approaches.

Keywords
Clustering, K-means method, Gaussian mixture model, AIDAS model, Advertisement analysis

1. Introduction

The commercial message (CM) is one of the most effective methods for advertising products and services (Belth, 1982). Companies define the appeal of their products and services to consumers by the broadcasting of CMs through the TV medium. CMs are expected to (1) create and nurture a good image of the company and its products for consumers, and (2) promote purchasing activities through consumer viewing (Belth, 1982). However, producing and broadcasting CMs without proper strategy cannot produce these intended effects. It is necessary to recognize the preferable psychological change in consumers from purchase situation data and purchase intention data, and then analyze the cause of the change to identify the appropriate target consumers and design the attractive CM for the same targets.

The effect of various kinds of CMs is studied mainly in the marketing field. For example, the effect of TV CMs is discussed by Panick et al. (2013), and recently, the technology of making decision of which channel and what time each CM should be broadcasted automatically is rapidly developed (Noller and Fabien, 2016; Jensen and Kristain, 2018). Additionally, studies on CMs of other media, such as advertisement on the newspapers (Patterson and Timothy, 2000), and web-banner advertisement (Lees and Healey, 2005) are widely derived. Most of the literatures are suggesting the effect of CMs based on the questionnaire survey gathering from consumers and analyzing the data. In this research, analysis was performed focusing on R-1, which has rich sample size, is a popular product in Japan, and broadcasts a CM with a clear and devised target on TV. Then
discuss the psychological change in consumers attributed to TVCMs. We analyze the effect of CMs based on the attributes of 3,000 consumers culled from questionnaire data and their TV browsing histories provided by Nomura Study Institute, Ltd. (NRI, 2018). For grasping the psychological state of consumers, we apply the attention, interest, desire, action, satisfaction (AIDAS) model (Esmael et al., 2011), which is applied in marketing analyses (Esmael et al., 2011). This model defines consumers’ five psychological states (i.e., attention, interest, desire, action, and satisfaction) based on questionnaire data. Further, we clarify the factors of CM that are expected to have effects on consumers with respect to each psychological state: consumers’ attribute data and TV browsing history data are processed using two clustering approaches, Gaussian mixture model (Bishop, 2006) and the k-means approach (Kim et al., 2008), respectively.

2. Data description and model

2.1 Data description

In this study, we analyze the CMs of a Japanese yogurt product using three datasets: consumer attribute data, TV programming data, and purchasing awareness and action data. We describe the detailed attributes as follows:

1) Consumer attribute data

The dataset is defined by three variables.

(i) Basic information (Categorical data)
- Sex: Male or Female
- Marital status: Unmarried, Married, Divorced or Widowed
- Presence of children: Yes or No

(ii) Physical problems of concern (Categorical data)
The consumer answers “Yes” or “No” to the following entities:
- Myopia / astigmatism
- Concern about eye fatigue
- Possibility of getting stiff shoulders
- Arthralgia
- Neuralgia
- Skin roughness
- Concern about spots on the skin
- Concern about catching a cold
- Concern about acne

(iii) Consumption value of lifestyle (Categorical data)
The consumer answers “Yes” or “No” to the following questions.
- I buy anything cheap and economical.
- I will consider buying it after carefully considering whether the price meets the quality.
- I buy good quality items, even if the price is somewhat high.
- I care about the reputation of what I use.
- I analyze various information before buying the product.
- I often choose items based on the reviews of people I know.

Note that, the data is consisted of categorical values.

2) CM viewing data

The count data of CM views of each consumer from January 30 to February 28, in 2017. The data were determined by televising the number of 649 TV programs. The view count data (continuous value data) were summarized using four time zones: view counts in the morning, the lunch, the evening, and the night.

3) Purchasing intention / purchasing situation data

The questionnaire survey with regard to purchasing intention and purchasing situation for the yogurt was conducted on two lunches: January 30, 2017 (the first survey) and February 28, 2017 (the second survey). The change of consumers’ purchasing intention and situation is observed by comparing the questionnaire scores at the two timing of each consumer.

2.2. AIDAS model

The AIDAS model represents the psychological state of consumer from the time when the consumer views the advertisement of the product up to the point when he/she is satisfied with the product (Esmael et al., 2011). The psychological/behavioral reactions of consumers to communication such as advertisements are defined as
following five situations:

**Attention**: Consumers who do not know the item

**Interest**: Consumers who do not want to buy the item and have not bought the item

**Desire**: Consumers who want to buy the item but have not bought the item

**Action**: Consumers who have bought the item once and more than twice, but do not want to buy again

**Satisfaction**: Consumers who have bought the item more than twice and want to buy again

The AIDAS model has been applied to various marketing analyses. For example, Mohammad et al., 2011, and Esmael et al., 2011 used the AIDAS model for analyzing the effect of CMs in advertising campaigns.

2.3. Soft clustering based on Gaussian mixture model

Gaussian mixture model (Bishop et al., 2016), obtained by linearly combining $K$ of the Gaussian distributions of random variable $\mathbf{x}$ is expressed as follows.

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k N(\mathbf{x} | \mu_k, \Sigma_k),$$

$$0 \leq \pi_k \leq 1, \sum_{k=1}^{K} \pi_k = 1$$

where $N(\mathbf{x} | \mu_k, \Sigma_k)$ is the Gaussian distribution with parameters of mean $\mu_k$ and covariance $\Sigma_k$.

Here, we introduce $K$ dimensional vector $\mathbf{z} = (z_1, \ldots, z_K)^T \in \{0, 1\}^K$ that expresses to which cluster among the $K$ clusters the data $\mathbf{x}_i$ belong. Then, the probability that $\mathbf{x}_i$ belongs to the $k$th cluster is expressed as follows.

$$p(z_k = 1 | \mathbf{x}_i) = \frac{\pi_k N(\mathbf{x}_i | \mu_k, \Sigma_k)}{\sum_{k=1}^{K} \pi_k N(\mathbf{x}_i | \mu_k, \Sigma_k)}$$

Based on this value, the data can be clustered stochastically. The expectation–maximization (EM) algorithm (Bishop et al., 2016) is used to obtain the parameters $p(\mathbf{z}), p(\mathbf{x} | \mathbf{z}), \mu_j, \Sigma_j, \pi_j$. The EM algorithm is a method for obtaining the maximum likelihood estimate value $P(\mathbf{x} | \theta)$ of the parameters in the latent variable model. The EM algorithm repeats the following two steps until the convergence condition is satisfied, to obtain the maximum likelihood estimate for the data. The likelihood $L$ is shown below.

$$L = \prod_{i=1}^{N} \prod_{k=1}^{K} \left[ \pi_k N(\mathbf{x}_i | \mu_k, \Sigma_k) \right]^{z_{ik}}$$

And the following are the two steps:

- **[E step]**
  
  We then fix the parameters of the probabilistic model and find the posterior probability (expected value) of the hidden variable $Z$. The hidden variable is shown below:

  $$\mathbf{Z} = (z_1, \ldots, z_N), z_i = (z_{i1}, \ldots, z_{iK})^T$$

  where

  $$z_{i1} = \begin{cases} 1 & (x_i \in k) \\ 0 & (x_i \not\in k) \end{cases}$$

- **[M step]**
  
  In this step, we substitute the posterior probability of the hidden variable into the Q function, and then find the parameter that maximizes the Q function (the expected value of the hidden variable is replaced by the posterior probability).

  By repeating the E and M steps, it is possible to cluster the data in a probabilistic manner. As this method enables clustering of the data probabilistically, it is applied for many marketing data analyses. For example, Shimizu et al. (Shimizu et al., 2017) used the Gaussian mixture model for clustering customers of fashion EC (Electric Commercial) sites (Ming-Hsuan et al., 1998), and Tezuka et al. (2008) used this model for clustering web contents.
3. Analysis procedure

The three datasets consumers’ attributes, CM viewing, and purchase intention / purchase situation data were analyzed according to the following procedure:

**Step 1: Understanding the psychology for the consumer items and change in statements**

First, we determined the psychology for each consumer item. The provided data, including the questionnaire results on purchase intention and purchase situation at the two time points, were evaluated based on the AIDAS model. Using the questionnaire survey data at the first time, the data were divided into five statements in terms of both purchasing intention and purchasing situation, as shown in Table 1. In comparing the survey at both the first and second times, we defined the preferable psychological change among consumers for each psychological state, as shown in Table 1.

**Step 2: Factor analysis of preferable psychological changes in consumers based on cluster analysis**

The factors of consumers’ psychological changes are assumed to originate from both TVCM viewing and consumer attributes. Therefore, we used two types of cluster analysis, Gaussian mixture model (Bishop et al., 2016) and k-means method (Kim et al., 2008, Tezuka et al., 2008), and then combined the results of the two analyses for the interpretation.

1. TV data showing consumers’ CM viewing history by the number of views for the four time periods (i.e., morning, afternoon, evening, and night) were clustered based on the Gaussian mixture model, and the data were divided into clusters probabilistically. We assumed that as the number of views varies from lunch to lunch, then the appropriate cluster differs from day to day. As such, soft clustering approach was deemed fitting for the analysis of data.

2. Consumer attributes data indicate basic information, physical problems of concern, and consumption problems obtained through the questionnaire survey. As the consumer attributes consist of categorical variables, we applied the k-means method for clustering the four preferable changes data.

3. The results of the two clustering methods are combined using the cross table by combining the two results obtained by the above two types of cluster analysis. This combination enabled the generation of clusters that take into account both the number of TV views and attributes of consumers. Then, we analyzed the difference of each cluster.

Furthermore, we identified the cluster that tended to show changes in psychological state by comparing the number of consumers who changed psychological states and did not change for each cluster. If the number of consumers with psychological state changes is more than that of consumers with no change, then the cluster can be interpreted as the well changed cluster.

**Step 3: Quantification of psychological state changes**

When comparing the number of consumers with or without psychological state changes for each psychological state, shown in Table 2; however, there is a problem that the number of consumers who changed or unchanged the psychological state changes are different. We encountered the problem of imbalance in the number of its indicating significant variation in the two values. Therefore, we defined the indicator of psychological changes as interpreting the two results of clustering. In each psychological state, considering both TVCM and consumer attributes, we calculated the degrees of consumers’ psychological changes belonging to the obtained cluster as follows. Let \( n \) be the number of TV clusters \( k \) \((k = 1, ..., n)\), and \( m \) be the number of consumer attributes \( j \) \((j = 1, ..., m)\).

Here, let \( p(z_k = 1|x_i) \) be the probability that customer \( i \) belongs to TV cluster \( k \). \( \delta_i \) denotes the indicator variable that scores 1 if consumer \( i \) changed his/her psychological state, scores 0 otherwise. Next, let \( \rho_{ij} \) be the indicator variable that if consumer \( i \) belongs to attribute cluster \( j \). Then \( \alpha_{kj} \), that is, the number of consumers that belong to TV cluster \( k \), attribute cluster \( j \), and changed the psychological state can be calculated as \( \alpha_{kj} = \sum_i p(z_k = 1|x_i) \delta_i \rho_{ij} \). On the other hand, the number of consumers that belong to TV cluster \( k \), attribute cluster \( j \), and did not change the psychological state can be calculated as \( \beta_{kj} = \sum_i p(z_k = 1|x_i) (1 - \delta_i) \rho_{ij} \).

Then the number of consumers who belong to TV cluster \( i \) and consumer attribute cluster \( j \) and changed their psychological state. Meanwhile, let the number of consumers who did not change their psychological state be denoted by \( \beta_{ij} \). Then, the total number of consumers with/without change is calculated as follows:

Total number of consumers with change is formulated as
\[ N_\alpha = \sum_{j=1}^{m} \sum_{k=1}^{n} \alpha_{kj}. \]

Table 1: Definition of psychological states from AIDAS model

| Purchasing intention | Purchasing situation | Psychological state (first survey) | Psychological state (second survey) |
|----------------------|----------------------|-----------------------------------|-----------------------------------|
| I want to buy        | 2 or more            | Attention                         | I want to buy                     |
| Neither              | 1 time               | Action                            | Attention                         |
| I don't want to buy  | Never                | Interest                          | Attention                         |

Table 2: Definition regarding change in psychological states

| Psychological state (first survey) | Psychological state (second survey) |
|-----------------------------------|-----------------------------------|
| Attention                         | With Change | Without change                  |
| Interest                          | Interest/Desire/Action/Satisfaction | Attention                        |
| Interest                          | Desire/Action/Satisfaction        | Interest                         |
| Desire                            | Action/Satisfaction               | Desire                           |
| Action                            | Satisfaction                       | Attention                        |

And the total number of consumers without change is as

\[ N_\beta = \sum_{j=1}^{m} \sum_{k=1}^{n} \beta_{kj}. \]

The indicator of psychological change for each psychological state is shown as below.

\[ I_{kj} = \frac{\beta_{kj}}{\alpha_{kj} + \beta_{kj}} \times \frac{N_\alpha + N_\beta}{N_\beta}. \]

Here, \( I_{kj} = 1 \) when \( \alpha_{kj} = N_\alpha \): \( \beta_{kj} = N_\beta \). That is, when \( I_{kj} \geq 1 \), it can be interpreted that the psychological state of more than half of the consumers of the cluster in the psychological state changed. In the following interpretation, we set the cluster target \( 0.75 \leq I_{kj} \leq 1.25 \) (it is easy to obtain the effect of CM) and find the factors of the target consumer. In the following, we focus on the cluster with psychological state change and the target cluster which is not a great indicator score, but not so a small indicator score.
4. Indicator of psychological changes and factor analytics for psychological state attention

The analyzed data were clustered according to the procedure described in Section 3. We calculated the indicator of psychological changes based on the results for each cluster. Then, we analyzed the factors of the psychological changes. We set the number of TV clusters $m = 4$ and that of the consumer attribute clusters $n = 4$, according to preliminary analysis. For brevity, we show only the results for psychological state changes in the attention state.

| TV clusters | Expected number of times to watch TV | Characteristic                  |
|-------------|-------------------------------------|---------------------------------|
|             | Morning | Lunch | Evening | Night |
| 1           | 0.22    | 1.23  | 0.43    | 0.31  | No TV viewing                        |
| 2           | 2.33    | 0.61  | 1.84    | 1.9   | Morning, evening, night              |
| 3           | 0.25    | 1.08  | 2.08    | 0.93  | Evening                              |
| 4           | 1.09    | 1.54  | 1.95    | 0.3   | Lunch, evening                       |

Table 3: Expected number and interpretation of TV viewing for each TV

| Consumer attribute cluster | 1  | 2  | 3  | 4  |
|----------------------------|----|----|----|----|
| Having no children         |    |    |    |    |
| Unmarried                  |    |    |    |    |
| No eye fatigue             |    |    |    |    |
| Near myopic astigmatism    |    |    |    |    |

Table 4: Characteristics of consumer attribute clusters belonging to the attention state

| Attention state as indicator of psychological change | Consumer attribute cluster | 1  | 2  | 3  | 4  |
|------------------------------------------------------|----------------------------|----|----|----|----|
| TV clusters                                          | 1  | 2  | 3  | 4  |
| 1                                                     | 0.00 | 0.22 | 2.04 | 2.01 |
| 2                                                     | 0.00 | 0.72 | 2.04 | 0.94 |
| 3                                                     | 0.00 | 0.31 | 2.04 | 1.10 |
| 4                                                     | 0.00 | 2.02 | 2.04 | 1.87 |

Table 5: Indicator of psychological changes in the attention state
Table 3 shows the expected number and interpretation of TV watching for each TV cluster. Table 4 lists the characteristics of the consumer attribute that are decided according to the importance k-means model (Wagstaff et al., 2005) for the attention state. Table 5 presents the indicator of psychological changes of the attention state when combining the analysis results of both TV clustering (the number is m) and consumer attribute clustering (the number is n) by calculating the expectation of the indicator of psychological change $I_{ij}$.

The results in Table 5 showed that the characteristics of consumers whose psychological state changed were unmarried and healthy (attribute cluster 3), and they had changed in all TV clusters. Moreover, the target consumers’ characteristics were having children and healthy (attribute cluster 4), and watching TV in the morning, evening, and night (TV clusters 2, 3); because we decided to see the target clusters where $0.75 \leq I_{ij} \leq 1.25$ (Shaded part of the table), that are not the great value and also not the small value. Therefore, there should have the potential of changement, and the approach for the cluster should effective for the The procedure of the cluster analysis and the calculation of the indicator of psychological changes are derived for every state, and in the following section, we interpret the results in detail. Note that, we set the number of consumer attribute clusters to be four for the psychological state of interest and action (also the attention), and ten for the psychological state of desire. The detailed description is not written in this paper due to the limitations of spaces.

Table 6 shows the expected number of psychological states changed or not for each of the TV cluster in the attention state and the consumer cluster.

| Cluster 1 | Number 16.15 | 8.12 | 16.73 | 23.63 |
| Cluster 2 | Number 0.29 | 0.01 | 0.01 | 0.52 |
| Cluster 3 | Number 11.53 | 6.75 | 8.20 | 12.58 |
| Cluster 4 | Number 0.03 | 0.02 | 2.10 | 0.52 |

For the discussion of the analysis results of the consumer attribute of changed both consumers and target consumers for each psychological state; attention, interest, desire, and action we analyzed the data set using the proposed model. We summarize the results by describing Table 7 and 8 described as the following procedure.

Firstly, we extract four variables of high importance in clustering customers from each psychological state (e.g., in the case of attention state, the four extracted variables are shown in Table 4). Then top-four variables were collected in all psychological states. As a result, there were six variables that became important in some of the psychological states. It is used as row information in the Table 7 and 8.

Next, we create the columns for each table. These tables focus on the feature of changed/ target consumers; therefore, we select the clusters having changed their psychological state. In the case of Table 7, because there were three clusters that changed in the attention state, four interest states, three desire states, and three behavioral states, the total number of columns is 13.

Then, we added the row of TV viewing time and put checkmarks on the corresponding customer information and attributes of the TV cluster. Finally, we checked the corresponded cells for each cluster with change or target cluster for each psychological state.

5. Interpretation of analysis results for every psychological state and suggestion of new CM based on the results

5.1. Characteristic analysis of consumers who showed changes in psychological states

For the discussion of the analysis results of the consumer attribute of changed both consumers and target consumers for each psychological state; attention, interest, desire, and action we analyzed the data set using the proposed model. We summarize the results by describing Table 7 and 8 described as the following procedure.

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Then, we added the row of TV viewing time and put checkmarks on the corresponding customer information and attributes of the TV cluster. Finally, we checked the corresponded cells for each cluster with change or target cluster for each psychological state.
The characteristics of the consumers with changes in psychological states in four levels, namely, the attention, interest, desire, and behavior states, are summarized in Table 7. Below is a summary. Note that the row shows the basic data attributes (Married and Having children), symptoms of concern attributes (Myopia and astigmatism, eye fatigue, stiff shoulder, and rough skin) which are selected that the importance value of k-means analysis exceeds to the certain value for each psychological state, and TV viewing time. The column represents the cluster(s), which has at least one element of state change. For example, Table 7 includes three classes in attention psychological state shown in Table 5 (classes 2, 3, and 5). Note that there are five classes of change in interest state, and three classes in desire state, and three classes in action state. The check marks (✔) are shown in the cells where the corresponding consumer attribute classes having the feature of basic data and symptoms of concern selected in Table 7. For example, in the attention state and the third column in Table 7, that is, the consumer attribute cluster No. 4 in Table 5, the cluster has the characteristics of having children and married, their column and the first and second rows are checked. The interpretation of Table 7 is as follows:

1. **Basic data:**
   - Many of the consumers were married. Consumers with changes in psychological states were strongly conscious of drinking the yogurt product in their family.

2. **Symptoms of concern:**
   - Most of the consumers were healthy; none of the symptoms of concern were observed. Originally, the yogurt was touted as effective for improving immunity, preventing influenza, improving gut flora, improving skin troubles, and preventing rheumatism. Despite changes in psychological states, the original message of the yogurt product seemed to have not been transmitted.

3. **CM broadcast time:**
   - Many of the consumers watched TV during the evening hours, and the number of viewers in the morning, afternoon, and night did not differ much. The number of CMs on air was numerous in the order of afternoon, evening, night, and morning. The number of advertisements was smaller in the afternoon compared with other times. This result should show that the effect is insignificant when the broadcasting time is during lunchtime.

### 5.2. Characteristic analysis of consumers who showed changes in psychological states

As same procedure of Table 8, we represent the summary of target consumers in Table 8 in the four states. The characteristics of the consumers with psychological state changes are summarized below.

1. **Basic data:**
   - Many single people tended to report psychological state change. Therefore, it is necessary to promote the product to single consumers for them to drink for the sake of their health.

2. **Symptoms of concern:**
   - Many consumers were concerned about disorders of any kind. Therefore, it is necessary to highlight the specific symptoms for which the yogurt can be deemed helpful.

3. **CM broadcast time:**

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**Table 7 Characteristics of consumers with psychological state**

| Consumers with changes | Att. | Int. | Des. | Act. |
|------------------------|------|------|------|------|
| Basic data             |      |      |      |      |
| Married                | ✔    | ✔    | ✔    | ✔    |
| Have children          | ✔    | ✔    | ✔    | ✔    |
| Symptoms of concern    |      |      |      |      |
| Myopia and astigmatism| ✔    | ✔    | ✔    | ✔    |
| Eye fatigue            | ✔    | ✔    | ✔    | ✔    |
| Stiff shoulder         | ✔    | ✔    | ✔    | ✔    |
| Rough skin             | ✔    | ✔    | ✔    | ✔    |
| TV viewing time        |      |      |      |      |
| Morning                | ✔    | ✔    | ✔    | ✔    |
| Lunch                  | ✔    | ✔    | ✔    | ✔    |
| Evening                | ✔    | ✔    | ✔    | ✔    |
| Night                  | ✔    | ✔    | ✔    | ✔    |

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Many reported watching TV in the morning and night, and then the evening, with the fewest in the afternoon. Therefore, the CM should be designed to be impressive for those watching in the morning, evening, and night. Moreover, it was found that the number of consumers watching TV during the lunch was overwhelmingly lower compared with any other time.

5.3. Proposal of new CM concept
In this subsection, we present the features of the current CM and propose a new CM, based on the discussion in subsections 5.1 and 5.2.

【Characteristics of the current CM】
The current CM (as of December 31, 2017) is centered on a newly married couple, focusing on Yoshida Saori, a Japanese female wrestling athlete. There are two scenes in the CM: a ticket gate at the station in the morning and a garden at a house in lunchtime. There are three main messages for health support: “It is effective for physical condition management,” “Lactic acid bacteria elicit strength,” and “Families prioritizing physical condition first.” This CM has a concept of encouraging viewers.

【Proposal for a new CM】
It is necessary to continue the promotion that the yogurt is a product for families. However, it is necessary to appeal to single people as well. Regarding physical condition management, although the message that the product is effective holds broad appeal, it is possible to highlight that this yogurt helps improve the immune system, including influenza prevention and improvement of gut flora, as well as brightens the skin and alleviates rheumatism. The CM has not mentioned anything about prevention. The CM has to present a more concrete message of health improvement.

As regards the concept of the CM, the current CM gives the impression that people drink it and encourages people to work out in the morning and afternoon. For the proposed new CM, there should be a CM for consumers who watch TV in the evening and at dinner time. In other words, the CM that is broadcast in the evening gives the message of treating those who have already worked hard.

6. Summary and future improvements
This study focused on Meiji’s Purobio yogurt R-1, which is familiar to many people, and proposed a new concept for a CM based on analyses of the effective features of the current CM. The analyses were based on TVCM data on consumer attributes, TV viewing data, and purchasing intention / purchasing situation data, conducted according to the following procedure.

First, to grasp the psychological state of consumers, we defined the psychological states by the AIDAS model using two datasets (i.e., purchase intent and actual purchase data). Second, as TV and consumer attribute data had difference features, we performed clustering by mixed normal distribution model for TV data and by k-means method for consumer attribute data, then combined the results. This approach enabled us to grasp the
characteristics of each group generated; the combined results identified the target consumers.

For the clustering results, in each psychological state, the change ratio of consumers who changed the psychological states belonging to clusters that considered TV viewing and consumer attributes was set as a mental state change indicator. Using the values of the psychological state change indicator, we identified the consumers (i.e., the cluster members) for whom TVCM viewing would be effective; in other words, the target consumers for whom the TVCM would be effective in the future. Subsequently, we made a proposal for a new CM by determining the characteristics of those people.

In future, it is necessary to clarify the features of each product and to consider CMs that are easy to achieve through verification of whether each product concept is communicated to consumers. As a method of grasping other characteristics, discriminant analysis (Toninelli et al., 2008) should be performed. This approach can demonstrate the differences in the characteristics of people with or without psychological state changes. In addition, by compressing the data in the low dimensional space based on principal component analysis, it is also possible to consider the characteristics of consumers who have or have not changed. We would like to regard these as future tasks in our study in this field.

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