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# A Study of Model of Kawaii Feelings for Evaluation of Products

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# A STUDY OF MODEL OF KAWAII FEELINGS FOR EVALUATION OF PRODUCTS

BY

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# Declaration of Authorship

I, Tipporn LAOHAKANGVALVIT, declare that this thesis titled, "A Study of Model of Kawaii Feelings for Evaluation of Products," and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at Shibaura Institute of Technology.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at Shibaura Institute of Technology or any other institution, this has been clearly stated.
- Where I have consulted the published work of other, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with other, I have made clear exactly what was done by others and what I have contributed myself.

Signed: ____________________________________

(Tipporn LAOHAKANGVALVIT)

Date: _______________________________________

# Abstract

For more than twenty years, Kansei engineering, which is a consumer-oriented methodology, has been recognized as an important part in a broad range of Japanese manufacturing. By making products to which kansei values are added, products can provide greater emotional fulfilment and make a larger impact on first impressions, which is a key to motivate consumer purchases. According to success of many kawaii products, kawaii is considered as one important kansei value for future product design and development. Therefore, this conduct this research to study kawaii feelings to clarify effectiveness of eye tracking to measure kawaii feelings, construct model of kawaii feelings, and employ eye movement indexes to clarify effective attributes to design kawaii products.

To clarify effectiveness of eye tracking to measure kawaii feelings, I experimentally evaluated the kawaiiness of illustrations while the eye tracking was being recorded. As the results, I clarified the relationship between kawaii feelings and eye movement indexes, and identified two new indexes. Therefore, I clarified that eye tracking was effectively used to evaluate kawaii feelings.

To construct models of kawaii feelings, I employed to products which were spoon designs and cosmetic bottles. First, I constructed the model for spoon designs using the Support Vector Machine (SVM) algorithm. Then, I continued to construct model for cosmetic bottles. However, the SVM algorithm has limitation that the feature extraction was necessary to prepare dataset as input for model construction, which could not be employed for cosmetic bottles because they have more complexed attributes. To solve the limitation, I employed the Deep Convolutional Neural Network (CNN) algorithm in which images can be used as input. Finally, I constructed model for cosmetic bottles, which shows that the

Deep CNN algorithm is useful for model construction if products have unknown sets or complexed attributes.

To clarify effective attributes to design kawaii products using eye tracking, I performed two steps. First, I defined candidates of effective attributes based on the results of the constructed models. For the model for spoon designs constructed by SVM algorithm, it can generate the attributes as output. However, the model constructed by Deep CNN algorithm cannot generate such output. Therefore, I developed a new method to evaluate the attributes, which was to modify images of cosmetic bottles and employed the model to predict the kawaiiness of those images. Second, I employed eye movement indexes identified in previous experiment to clarify effective attributes for both spoon designs and cosmetic bottles. Finally, I clarified the relationship between attributes and eye movement indexes. The results clarified effective attributes to design kawaii products and confirmed the effectiveness of using eye tracking for product evaluation.

In conclusion, I confirmed that I achieved all of my research goals to clarify the relationship between kawaii feelings and eye movement indexes, constructed model of kawaii feelings, and clarified effective attributes obtained from the model using eye movement indexes. The findings of this thesis are also applicable to other researches to study other products and other kansei values.

“We don’t look backwards for very long.
We keep moving forward, opening up new doors, and doing new things,
because we’re curious…and curiosity keeps leading us down new paths.”

**– Walt Disney –**

# Acknowledgments

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# Abbreviations

| | | |
|---|---|---|
| ANN | = | Artificial neural network |
| AOI | = | Area of interest |
| CNN | = | Convolutional neural network |
| EEG | = | Electroencephalography |
| EMG | = | Electromyography |
| METI | = | Ministry of Economy, Trade and Industry |
| MS | = | Millisecond |
| RBF | = | Radial basis function |
| SVM | = | Support vector machine |

# Chapter 1

# Introduction

## 1.1 Motivation

For more than twenty years, Kansei engineering, which is a consumer-oriented methodology, has been recognized as an important part in a broad range of Japanese manufacturing. It is defined as “a kind of technology that translates the customer’s feeling (kansei) into design specifications” [1]. By making products to which kansei values are added, products can provide greater emotional fulfilment and make a larger impact on first impressions, which is a key to motivate consumer purchases [2].

Based on their benefits, in 2007 the Japanese Ministry of Economy, Trade and Industry (METI) proposed kansei value as a new value axis, becoming the fourth most critical characteristic of industrial products after function, credibility, and cost [3]. Examples of kansei values that have been widely applied to products are enjoyment, coolness, and user friendliness. Kawaii or Kawaiiness is also considered as one kansei value that denotes such positive connotations as cute, lovable, and charming and plays an important role in the worldwide success of many products, such as Hello Kitty [4] and Pokémon [5]. Based on this success, I believe that kawaii will be a key factor for future product design and development.

Based on kansei engineering approach, the products should be designed based on the customer's feeling [1]. Therefore, this research focuses on study of kawaii feelings together with product attributes which cause the feelings. Generally, "kawaii" is an adjective related to physical characteristics or attributes of the products. However, the human emotion on perceiving kawaiiness from the products is also focused, which is called as "kawaii feeling" in this research. The importance of product design focusing on emotional aspect is not limited to only kawaii feelings, but also various other products and other feelings as described in the following examples.

- Design of children's wheelchair that is fun or has a positive emotional impact [6]
- Design of ladies' shoes based on comfort [7]
- Design of car interior to understand the characteristics of styling for a desired impression [8].

In kansei-related researches, many measurement methods have been employed to measure kansei. Such subjective evaluation as questionnaire is one of commonly used methods because it has many advantages. However, human's emotional states are implicit and usually expressed unpredictably, which are difficult to measure only by using only questionnaire [9]. Therefore, many researches employed such objective methods as measuring biological signals [10], which can provide quantitative output and usually be able to catch unconscious and immediate human's responses [11]. Researches [12], [13], and [14] have studied kawaii feelings by employing various biological signals such as electrocardiogram (ECG), Electroencephalogram (EEG), and eye tracking. Eye tracking has been widely employed in various research fields including cognitive and experimental psychology, human-computer interaction, and product development. Many researches revealed that it is effective to recognize human emotional states. However, it has not been scrutinized yet to study kawaii feelings. Therefore, it should be employed in kawaii-related research to clarify the eye movement indexes related to kawaii feelings.

Researches have explored kawaii attributes for designing kawaii products such as shape, size, color, texture, and tactile sensation [15]. They systematically analyzed kawaii attributes, which is a bottom-up approach that the attributes must be specified from the first. This approach is considerably difficult to employ for many kawaii products since they usually contained various attributes. Instead, kansei modeling, which is top-down approach, has been proposed. In many kansei-related researches, they proposed kansei models and used the models to evaluate the user's feelings. Therefore, the model of kawaii feelings should also be proposed and used to evaluate kawaii products as well.

## 1.2 Problem Statement

Based on the motivation, there are several problems. I discussed them and the proposed solution as follows:

1. Clarification of relationship between kawaii feelings and eye movement indexes

Even though eye tracking has been successfully employed in many researches, only few researches employed it to study kawaii feelings. In addition, there were no researches that clarify relationship between kawaii feelings and eye movement indexes. Therefore, it remains unclear about their relationship. In addition, the eye movement indexes that can be used to evaluate kawaii feelings are still unknown. Therefore, eye tracking should be employed to study kawaii feelings in order to clarify their relationship and propose effective eye movement indexes, which can confirm the effectiveness of using eye tracking to evaluate kawaii feelings.

2. Construction of Model of Kawaii Feelings

Even though many researches have constructed models of various emotions, the model of kawaii feelings has never been proposed yet. Therefore, several issues on construction of model of kawaii feelings remain unclear. First, the possibility to construct the model for a specific product is needed to be clarified. Then, method for model construction as well as the possibility to employ the same method for other products should be clarified.

3. Clarification of effective attributes to design kawaii products

Even though the model of kawaii feelings can be constructed, the effective attributes to design kawaii products cannot be clarified yet. Since clarifying the effective attributes is very important step to provide suggestion to design kawaii products, it is necessary to explore the method to obtain the effective attributes from the model. From the solution of the first problem statement, eye movement indexes related to kawaii feelings should be clarified. Then, they can be employed to clarify the relationship with attributes in order to propose effective ones to design kawaii products.

## 1.3 Research Questions

Based on the problem statement, several issues related to the clarification of the effectiveness of using eye tracking to evaluate kawaii feelings and the construction of model of kawaii feelings must be solved.

1. Is there a relationship between kawaii feelings and eye movement indexes? If so, which eye movement indexes can be used to clarify their relationship?
2. Are there any possibilities to construct model of kawaii feelings? If so, what kind of products and methods are appropriate to employ for model construction?
3. Which method can be used to evaluate the candidates of effective attributes from the constructed model? Also, how to clarify effective ones to design kawaii products?

## 1.4 Research Goals and Contribution

According to the problem statements and research questions, eye tracking should be taken into account to study kawaii feelings. The research goals and contribution are described below.

1. Clarifying the relationship between kawaii feelings and eye movement indexes,

and also identifying new eye movement indexes related to kawaii feelings

2. Constructing models of kawaii feelings and clarifying appropriate products and methods for model construction
3. Clarifying effective attributes to design kawaii products using the constructed model and eye movement indexes

## 1.5 Organization of Thesis

This thesis consists of nine chapters including this one, which are organized as illustrated in Figure 1.1.

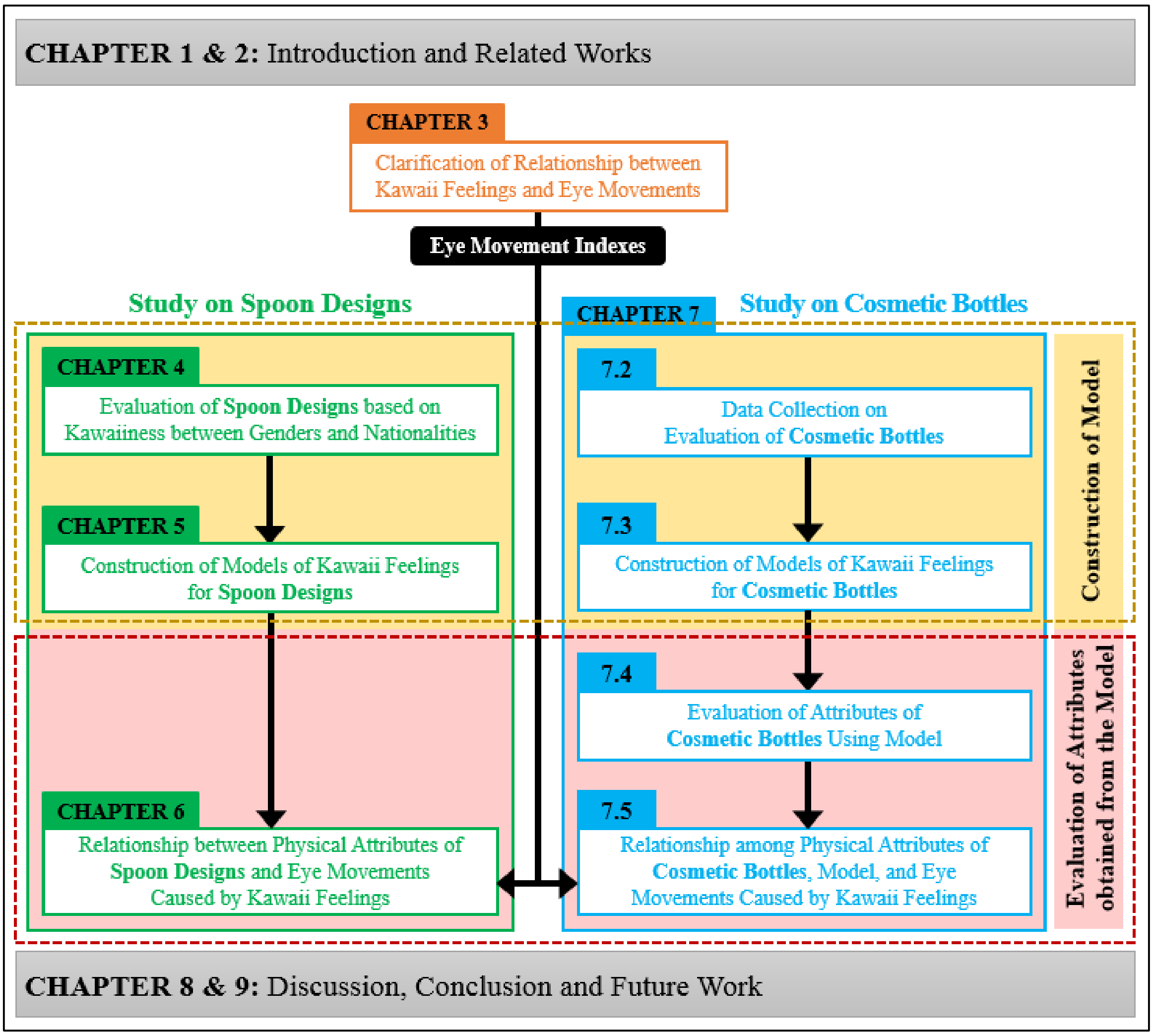



**Figure 1.1** Structure of this thesis

Chapter 2 presents related works on kansei engineering and kawaii-related researches.

Chapter 3 presents a clarification of relationship between kawaii feelings and eye movement indexes which are later employed in Chapter 6 and the last section of Chapter 7.

Chapters 4, 5 and 6 present studies on spoon designs. Chapter 4 presents an evaluation of spoon designs based on kawaiiness, which is a step to collect data for model construction in Chapter 5. Next, Chapter 5 presents a construction of model of kawaii feelings for spoon designs by Support Vector Machine (SVM) algorithm, which suggested candidates of effective attributes to design kawaii spoons. Finally, Chapter 6 presents a clarification of effective attributes of kawaii spoon designs using eye movements. This chapter employed eye tracking indexes obtained from Chapter 3 to evaluate spoon designs and their attributes obtained from Chapters 4 and 5.

Chapter 7 presents a study on cosmetic bottles. This chapter is divided into four sections. First, Section 7.2 presents an evaluation of cosmetic bottles based on kawaiiness, which is a step to collect data for model construction in Section 7.3. Next, Section 7.3 presents a construction of model of kawaii feelings for cosmetic bottles using the Deep Convolutional Neural Network (CNN) algorithm. Then, Section 7.4 presents an evaluation of attributes for cosmetic bottles using the constructed model. Finally, Section 7.5 presents a clarification of effective attributes of kawaii cosmetic bottles using eye movement indexes obtained from Chapter 3.

Chapter 8 presents a discussion of this thesis, especially the method to solve the problems and achieve the research goals. Also, this chapter discusses its news findings.

Chapter 9 concludes this thesis and future work.

# Chapter 2

# Related Works

## 2.1 Kansei Engineering

Kansei engineering [1] is a consumer-oriented methodology for product development. It was founded by a Japanese psychologist, Professor Mitsuo Nagamachi, in the early 1970s. A Japanese term “kansei” has a broad meaning. According to Japanese-English dictionaries, it is translated into sense, sensitivity, sensitiveness, and sensibility. From an engineering perspective, its definition is specifically given as “the impression someone gets from a certain artifact, environment or situation using all their senses of sight, hearing, feeling, smell, taste as well as their recognition” [16]. Based on [1], kansei engineering is defined as “a kind of technology that translates the customer’s feeling (kansei) into design specifications.” In recent years, kansei engineering is also known as affective [1] or emotional [17] engineering.

In addition, there are similar researches in a field close to kansei engineering. Picard started a branch of affective computing which firstly focused on the interaction between machine and emotional state of humans [18]. Fukuda et al. have conducted researches in a field of emotional engineering which focuses on user-centric design proposing that emotion and individual human needs become more important [19]. Even though these researches used different terms, e.g. kansei, affect, and emotion, all of them indicate the importance to consider kansei as important factor in the design of products and systems.

Figure 2.1 illustrates a structure of kansei engineering. As proposed in [1], such physiological signals as eye movements, Electroencephalography (EEG), Electromyography (EMG), are important to measure kansei and achieve kansei product design. Only one or the combination of them can be used for the measurement. However, it is necessary to firstly confirm that it can successfully reach the customer's kansei.

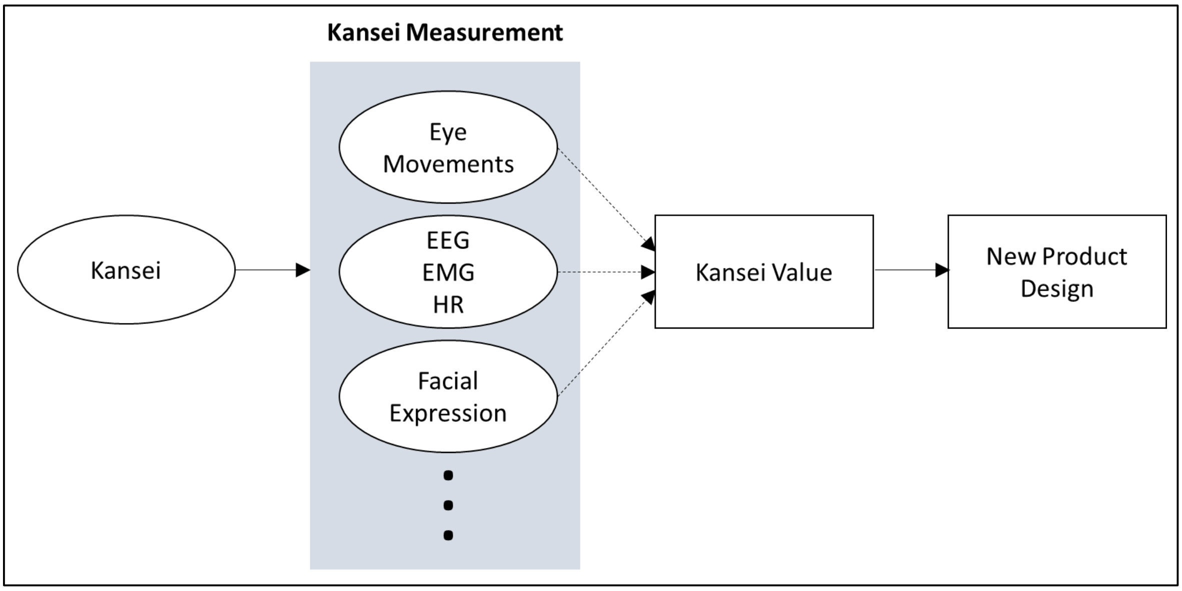



**Figure 2.1** Structure of kansei engineering [1]

## 2.2 Kansei Value

Kansei engineering has been recognized as an important part in a broad range of Japanese manufacturing, for example, automotive (e.g. Nissan, Mazda), apparel (e.g. Wacoal), electronic and home appliances (e.g. Canon, Sharp, Panasonic), cosmetics (e.g. Shiseido) [20]. In 2007, the Japanese Ministry of Economy, Trade and Industry (METI) proposed kansei value as a new value axis, becoming the fourth most critical characteristic of industrial products after function, credibility, and cost [3] (Figure 2.2). When added to ordinary products, kansei values can increase their economic worth. By making products to which kansei values are included, products can provide greater emotional fulfillment and make a larger impact on first impressions, which is a key to motivate consumer purchases [2].

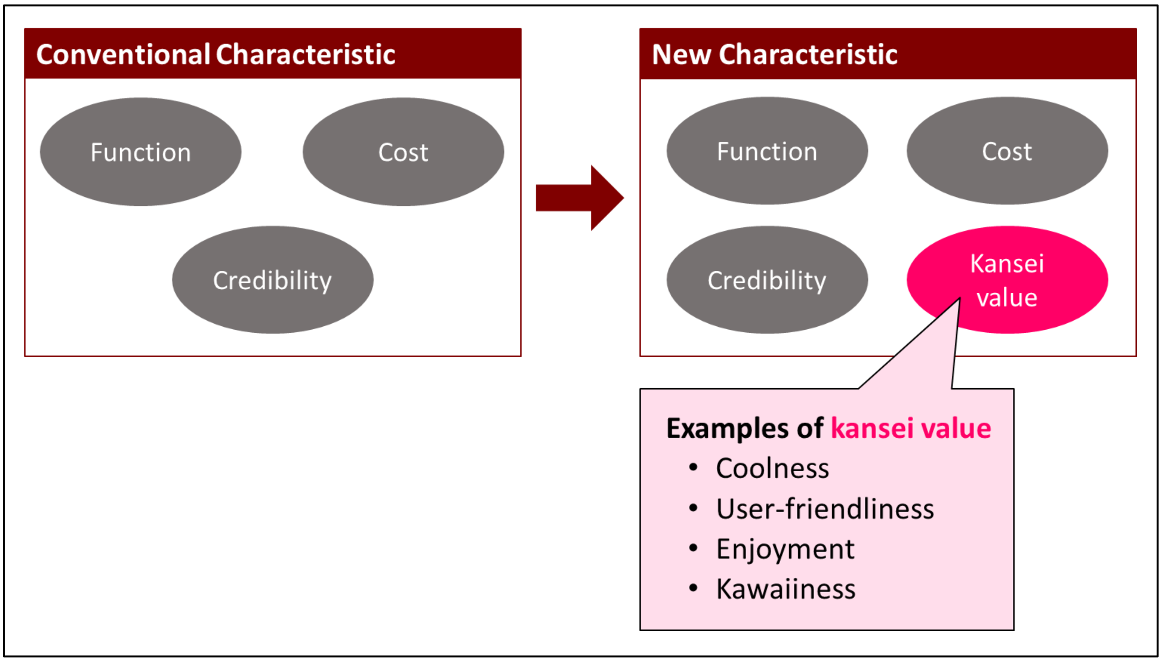



**Figure 2.2** Characteristic of industrial products in which kansei value is proposed as new value axis

Examples of kansei values that have been widely applied to products are enjoyment, coolness, and user friendliness. Kawaii (or Kawaiiness) is also considered as one kansei value that plays an important role in worldwide success of many products [21]. Based on their success, kawaii is taken into account as a key factor for future product design and development.

## 2.3 Kawaii

Kawaii is a Japanese term that denotes such positive connotations as cute, lovable, and charming. This term is commonly used to describe styles, fashions, and personalities, but quite unfamiliar in the context of emotion. To discuss this issue, research [22] confirmed that kawaii feeling does exist and has biological significance. It is usually described as an emotional response to infantile, baby-like, delicate, and heart-warming characteristics [23], [24], [25].

Researches have explored various attributes for designing kawaii products such as shape, color, size, texture, and tactile sensation [15] (Figure 2.3) Table 2.1 summarizes the “kawaii rules” proposed by [15], which suggested attributes for kawaii product design.

Researches [26], [27], [28] emphasize the importance of visual appearance of consumer’s choice of products that the decisions are often made based on the aesthetics when the candidates of product are similar in functions. Therefore, focusing on visual appearance for product design is considered important to increase its kansei value. The visual appearance can be defined as product properties or attributes, which include size, shape, color, texture, material, glossiness, transparency, and so on [28], [29].

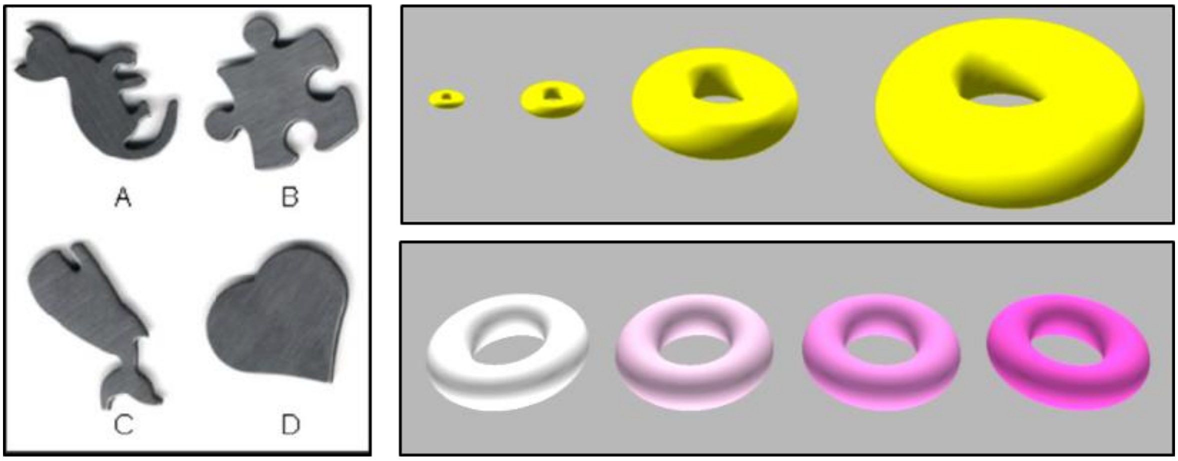



**Figure 2.3** Examples of attributes to design kawaii products [15]

**Table 2.1** Summary of “kawaii rules” proposed by [15]

| Attribute | Value of Attribute | |
|---|---|---|
| | Kawaii | Non-kawaii |
| Shape | Curved (e.g. sphere, torus, circle) | Straight-lined |
| Color | Warmer | Colder |
| Brightness | Higher | Lower |
| Saturation | Higher | Lower |
| Texture | bushy, fluffy, soft, “like animal hair” | Crumbly, hard, rough |

In recent kawaii-related researches, they did not focus only on the attributes, but also the overall impression of kawaii products. Research [30] proposed to design kawaii spoons for the elderly to help increase their appetite. Research [31] clarified that kawaii things narrow an attentional focus, which will be useful to improve careful behavior in many situations such as driving and office work. Research [32] proposed various factors that influenced the cuteness perception such as facial expression, posture, body shape, clothing, eye roundedness, etc.

## 2.4 Kansei Measurement

In kansei-related researches, many measurement methods have been employed to measure kansei. Such subjective evaluation methods as questionnaires are commonly used for the measurement because it has many advantages. However, human's emotional states are implicit and usually expressed unpredictably, which are difficult to evaluate just by using subjective evaluation methods [9]. To solve those difficulties, many researches employed such objective evaluation methods as measuring physiological signals [10], which can provide quantitative output and usually be able to catch unconscious and immediate human's responses [11].

There are various kinds of physiological signals such as electrocardiogram (ECG), Electroencephalogram (EEG), and eye tracking. They have been widely used in various researches especially for emotion recognition based on the circumplex model of affect developed by James Russell [33]. Several researches used ECG signals to recognize various emotions such as joy, anger, sadness, happy, relaxed, and excitement [34], [35], [36], [37]. In addition, EEG signals have also been widely used to recognize emotions and represent cognitive functions such as distraction, fatigue, and concentration [38], [39], [40], [41]. In kawaii-related researches, [12], [13], and [14] have systematically studied kawaii feelings by employing various physiological signals such as electrocardiogram (ECG), Electroencephalogram (EEG), and eye tracking. From the significant results of various researches including kawaii ones, they clarified the possibility of using physiological signals as methods to effectively capture the kawaii feelings.

As mentioned above, various physiological signals were effectively used for emotion recognition. However, this research focuses only on eye tracking according to its various advantages over other physiological signals as follows:

- Can dynamically capture user's attention more directly than other biological signals, which is useful especially for product design [42].
- Requires quick set-up and no complicated hardware configuration [43].
- Has affordable price and portability, making it a practical device for future research in product design [44].

Eye tracking has been widely and successfully used in various research fields including cognitive and experimental psychology, human-computer interaction, and product development, which revealed that it can effectively recognize emotional states and implicit needs of human.

Several researches employed eye tracking for emotion recognition, in which various eye movement indexes were effectively used. Some examples are described as follows:

- Studies on behaviors influenced by emotional pictures revealed that longer gaze duration and larger pupil size were induced by emotional or interesting pictures [45] and [46].
- Children's preferential attention to various baby schema images were induced cuteness perception and gaze allocation [47].
- In decision-making tasks, the first and last fixations were more likely to be made toward the chosen alternatives [48].
- Person's interest level and the focus of attention were drawn by eye position tracking and such indirect measures as number of fixations and fixation duration [42].
- User interaction and eye gaze behavior were analyzed within different contexts such as advertising, websites, television news, and video games, by measuring fixations and saccades [49].

In addition, eye tracking has been involved in many researches related to product design and development. They show that the strong advantage of eye tracking, which is directly capture user's attention [42], is useful for the detailed analysis of the design of product features as described in the following examples.

- Evaluation the design of wristwatches [50] analyzed fixation duration, saccades, and scan paths to determine parts of product that attract user attention and evoke positive emotions.
- Design evaluation of mobile phones revealed possible relationship between people's gazes and preferences in the designs by analyzing average number of fixations [51].
- Perception evaluation analysis of beer bottles with eye tracking revealed attentional focus on the product by using total fixation duration and gaze patterns, and proposed that fixations are the most commonly used parameter when assessing consumer's attention [52].
- Visual cognitive features on the design of car utilizing the front appearance was studied to analyze the main area of interest of consumers [53].
- Investigation of relationship between the product elements to design fuel tanker was performed by employing fixation duration, fixation transition rate, and number of fixation [54].
- Evaluation of eye movement patterns on Yellow Pages advertising revealed that such features as color and font boldness caused people to notice an ad [55].
- Analysis of drug labels using eye tracking revealed that text positioning, clear background, and consistent font caused lower information processing demands [56].

Usually, eye tracking is not used in daily life, but mostly employed in researches. However, there are various real situations that eye tracking has been applied. For example, in retail environment, it can be used to investigate consumer's attention to the product placement [44]. Study of the visitors' experiences in a museum used eye tracking to measure their attention to artworks [57]. Eye tracking was employed in e-learning system to detect interest and boredom, which is essential for productive learning [58]. Also, it was proposed to be integrated in a car system to provide safer driving environment such as a distraction calculation [59]. Finally, it can be an important assistive technology for people with disabilities that it can help people to use their eye movements instead of hand or other movements in controlling tasks [60].

According to various researches that employed eye tracking for emotion recognition, I confirmed that eye tracking has potential to be effective method to measure kawaii feelings by employing various eye movement indexes. In addition, various applications of eye tracking in product design and development confirmed that it can be effective method to evaluate kawaii products. Finally, the applications of eye tracking in real environments show the possibility that it has potential to be used for evaluation of kawaii products in real situations. For example, the eye tracking can be installed in a clothing store to help customers make decision on purchasing choices for more kawaii clothes.

# Chapter 3

# Clarification of Relationship between Kawaii Feelings and Eye Movements

## 3.1 Background

In researches related to emotion, eye tracking is considered as effective method. However, few researches have employed eye tracking to study kawaii feelings. The research [61] experimentally determined kawaii illustrations by recording eye movements while participants chose the most kawaii illustration from six on display. Before the six illustrations were displayed, the previous page showed cross sign (+) to fixate the eye movements at the center of the display. Therefore, the eye tracking result showed the purple circle with the number “0” at the white area which means that the participant firstly focused on that position of the display. The result clarified the differences between favorite and most kawaii illustrations as well as the differences in preferences between genders. However, the accuracy of the eye tracking result from a calibration-free eye tracking device was insufficient to scrutinize and clarify the relationship between kawaii feelings and eye movement indexes. Also, the six illustrations were shown simultaneously, which complicated the eye movements (Figure 3.1).

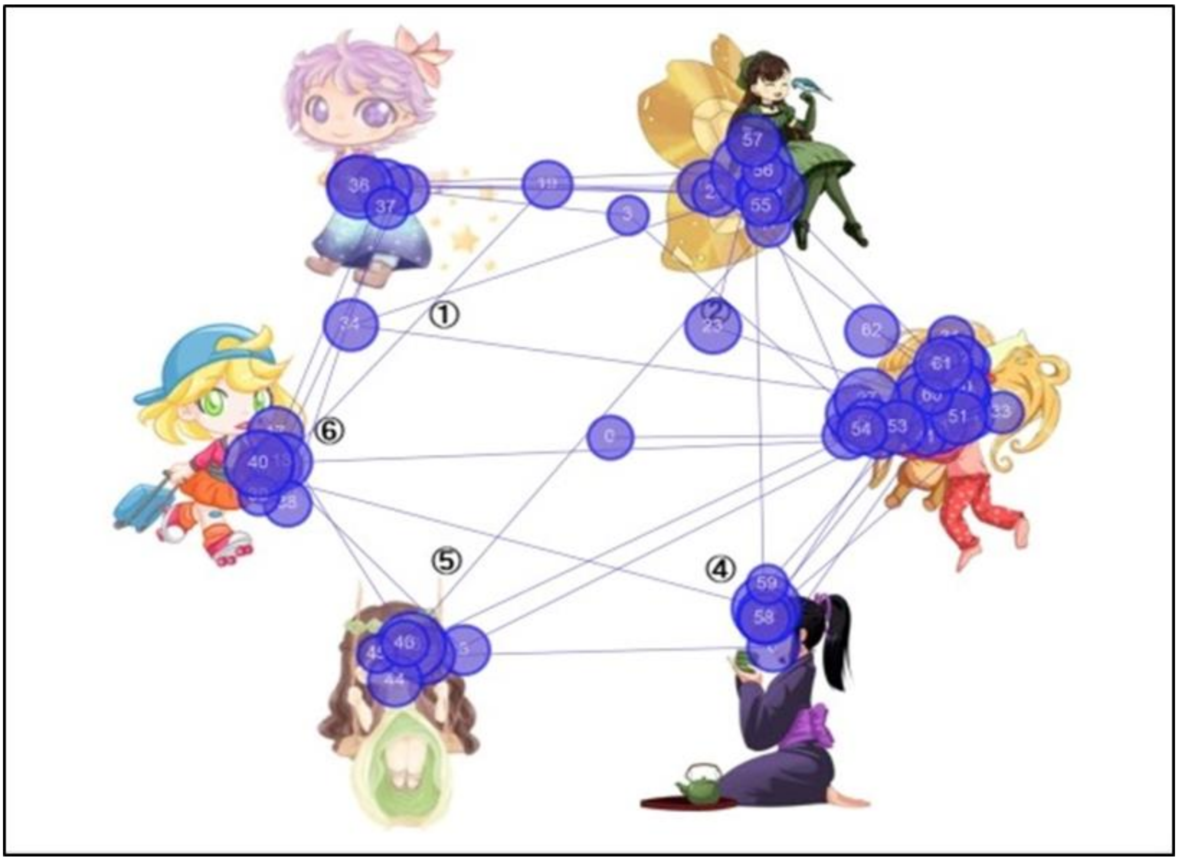



**Figure 3.1** Eye movements recorded during an evaluation of six kawaii illustrations

Even though the research [61] did not clarify the relationship between kawaii feelings and eye movement indexes, the results suggested the possibility of using eye tracking as a method to evaluate kawaii feelings. Therefore, I continued to use eye tracking for this research to clarify its effectiveness for evaluating kawaii feelings.

This chapter presents a study on clarification of the relationship between kawaii feelings and eye movement indexes [62]. Based on the problem of previous research [61], I designed and performed an experiment on the evaluation of kawaii illustrations.

## 3.2 Experiment Method

### 3.2.1 Visual Stimuli

Since the word "kawaii" is often used to describe girls or characters, the previous research [61] used girl illustrations in their experiment, which are usually easiest to understand by every genders and generations. In addition, the illustrations had certain differences, which were appropriate stimuli for eye tracking analysis. Therefore, I used the same six kawaii illustrations as visual stimuli (No.1 to No.6) (Figure 3.2), which were originally drawings to eliminate potential preference bias from famous cartoon characters. Sharp sign (#) with number denotes illustration number that represents six illustrations, #1, #2, #3, #4, #,5, and #6, as shown above each illustration.


**Figure 3.2** Original kawaii illustrations

### 3.2.2 Comparison System

I designed a comparison system to solve the problem of previous experiment [61] as follows.

1. The illustrations were displayed in pairs at a time randomly selected from the six.
2. The illustrations were enlarged to show their details more clearly.
3. Participants' eyes were calibrated before recording the eye movements.

The comparison system was modified from a system that evaluated kawaii ribbons [63]. The illustrations were displayed in pairs with left-right counterbalanced. The total number of compared pairs was 30 times. All of the system content was described in Japanese. The structure of the system is described as follows:

1. Top page: questionnaire explanation
2. Selection of participant's gender and age
3. Explanation of illustration selections: the illustrations were displayed in pairs for five seconds. Selection of more kawaii illustrations was performed using the keyboard's left or right arrow keys.
4. Illustration selection: 30 pairs were randomly displayed for each participant. An example of this page's screenshot is shown in Figure 3.3.
5. Questionnaire: three subjective questions were asked: reason for selecting the illustrations (free description), most kawaii illustration, and favorite illustration.
6. After the participants submitted their questionnaires, the results of the illustration selections and the questionnaires were saved in a database.

**Figure 3.3** Example of page in comparison system showing two illustrations and selection arrows

### 3.2.3 Experimental Setup

Figure 3.4 shows the experimental setup. The comparison system was accessed from the eye tracking system through a web browser, i.e., Google Chrome, whose system ran on a separate PC due to limited resources. The eye tracking system employed the EyeTech TM3 non-intrusive eye tracker (EyeTech Digital Systems, Inc.) (Figure 3.5) and QG-PLUS software (DITECT Co., Ltd.) to record the eye movements and display the eye tracking data. I used a 19-inch LCD monitor with resolution of 1280 x 1024 pixels. The experiment scene is shown in Figure 3.6.

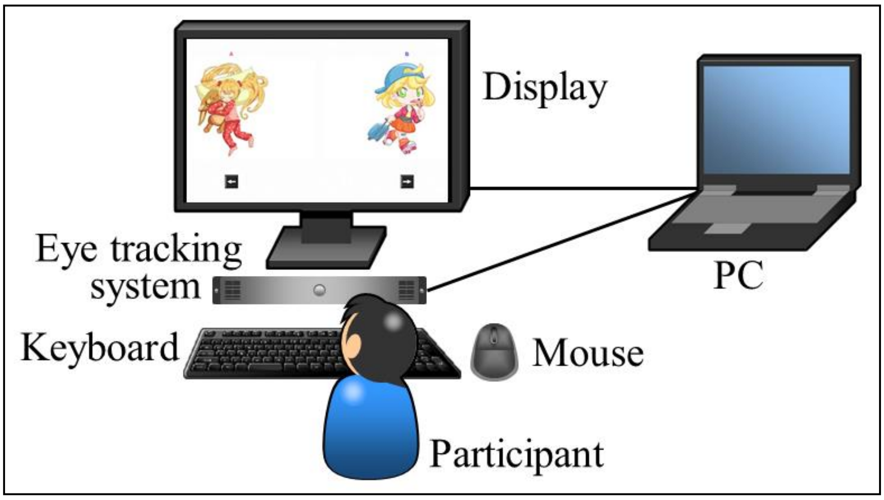



**Figure 3.4** Experimental setup where participant looks at illustrations on PC monitor while eye tracking system records his eye movements


**Figure 3.5** EyeTech TM3 non-intrusive eye tracker

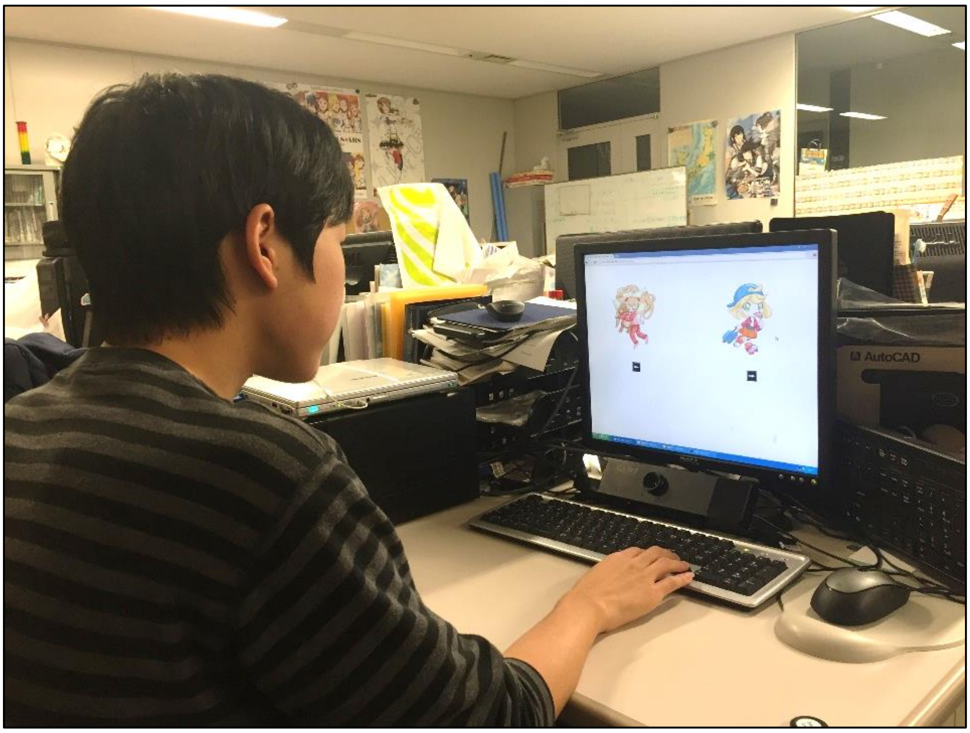



**Figure 3.6** Experiment scene

### 3.2.4 Experimental Procedure

The following are the experimental procedures:

1. Participants sit on chairs in front of the PC.
2. They read the explanation sheet.
3. Experimenter calibrates the eyes of the participants.
4. Experimenter shows the comparison system and starts recording the eye tracking.
5. They answer their general information: gender and age.
6. They select from 30 pairs of illustrations.
7. They answer the questionnaires on three questions as follows:
   - Which is the most kawaii illustration?
   - Which is the favorite illustration?
   - What is your reasons to select kawaii illustrations? (free description)
8. Experimenter stops recording the eye tracking.

# 3.3 Experimental Results

## 3.3.1 Participants

As shown in Table 3.1, the experiment was performed with 38 Japanese volunteers: 14 males in their 20's, 10 females in their 20's, and 14 females over 65 years old. However, only 21 bits of eye tracking data (7 males in their 20's, 8 females in their 20's, and 6 females over 65 years old) were successfully collected. The other 17 participants without eye tracking data were not included in eye tracking analysis due to two reasons: (1) ceiling light and sunlight affected to eye tracking device which failed to calibrate or track eye movements, and (2) some participants used a mouse instead of a keyboard during the selection of illustrations which might cause slower eye movements and increase cognitive workload for the hand-eye interactions.

**Table 3.1** Number of participants with/without eye tracking data divided by participant groups

| Participant Group | Number of Participants | |
|---|---|---|
| | **With Eye Tracking Data** | **Without Eye Tracking Data** |
| Male 20's | 7 | 7 |
| Female 20's | 8 | 2 |
| Female over 65 | 6 | 8 |
| Total | 21 | 17 |

## 3.3.2 Cumulative Results

The cumulative results (the kawaii scores) were collected from the total number of illustration selections from 38 participants and used to rank the illustrations. The rankings, based on cumulative kawaii scores, are shown in Table 3.2. The rankings among the three participant groups were quite different.

**Table 3.2** Rankings based on kawaii scores, which are cumulative values as total number of selections. Sharp sign (#) with number denotes illustration number. Number inside parentheses () show data used for ranking kawaii scores.

| Participant Group | Ranking of illustration: kawaii scores | | | | | |
|---|---|---|---|---|---|---|
| | 1st | 2nd | 3rd | 4th | 5th | 6th |
| Male 20's | #3 (90) | #2 (79) | #4 (73) | #6 (63) | #5 (59) | #1 (56) |
| Female 20's | #2 (69) | #4 (60) | #1 (51) | #3,#6 (41) | | #5 (38) |
| Female over 65 | #1 (99) | #3 (77) | #6 (69) | #2 (67) | #4 (63) | #5 (45) |

### 3.3.3 Questionnaire Results

The questionnaire results consist of three items:

1. Number of illustrations selected as the more kawaii
2. Number of illustrations selected as favorites
3. Reasons for selecting more/favorite illustrations (free description)

The results of questionnaire items 1 and 2 were used to rank the illustrations, as shown in Table 3.3 and Table 3.4. The ranking results showed that the first and last rankings of Table 3.2 and Table 3.3 are similar. Furthermore, the first rankings for all of the participant groups of Table 3.4 were the same, which shows that all three participant groups preferred illustration #4.

**Table 3.3** Ranking based on illustrations selected as more kawaii. Details are identical as described in Table 3.2, where data used for ranking are "number of illustrations selected the most kawaii" from questionnaire item 1.

| Participant Group | Ranking of illustration: kawaii scores | | | | | |
|---|---|---|---|---|---|---|
| | 1st | 2nd | 3rd | 4th | 5th | 6th |
| Male 20's | #3,#4 (4) | | #6 (3) | #2 (2) | #5 (1) | #1 (0) |
| Female 20's | #2 (4) | #3,#6 (2) | | #4,#5 (1) | | #1 (0) |
| Female over 65 | #1 (4) | #3,#6 (3) | | #2,#4 (2) | | #5 (0) |

**Table 3.4** Ranking based on illustrations selected as favorites. Details are identical as described in Table 3.2, where data used for ranking are "number of illustrations selected as favorites" from questionnaire item 2.

| **Participant Group** | **Ranking of illustration: kawaii scores** | | | | | |
|---|---|---|---|---|---|---|
| | **1st** | **2nd** | **3rd** | **4th** | **5th** | **6th** |
| Male 20's | #4 (5) | #3 (3) | #2,#5,#6 (2) | | | #1 (0) |
| Female 20's | #4 (5) | #2 (4) | #6 (1) | #1,#3,#5 (0) | | |
| Female over 65 | #4 (6) | #3 (3) | #1,#2 (2) | | #6 (1) | #5 (0) |

The participants also described why they selected the illustrations in questionnaire item 3. I summarized the results based on the number of times that they mentioned each area in the illustrations as follows:

- Most participants selected the illustrations based on eye size, face shape, and hairstyle.
- Other selection reasons mentioned the total atmosphere, colors, gestures, costumes, facial expressions, and the baby-like deformed shape of the illustrations.

### 3.3.4 Results of Eye Tracking Data

Based on the rankings of the cumulative results, I recalculated and ranked only data from the 21 participants whose eye tracking data were successfully recorded.

I employed fixation and Area of Interest (AOI). Fixation is defined as the eye state when it remains still or looks at the same spot over a period of time (threshold) that was set to 200 milliseconds (ms). The threshold was set based on average fixation durations which last about 200-300 ms [64], [65], [66]. AOI is defined as the area used to include or exclude certain segments from analysis. For this experiment's analysis, I defined two AOIs for the left-side and right-side illustrations (Figure 3.7) and created AOIs as ellipses based on the size of illustration #4, which is the widest and tallest. Since the shape and the size of all of the other illustrations were identical, their analysis areas were balanced.

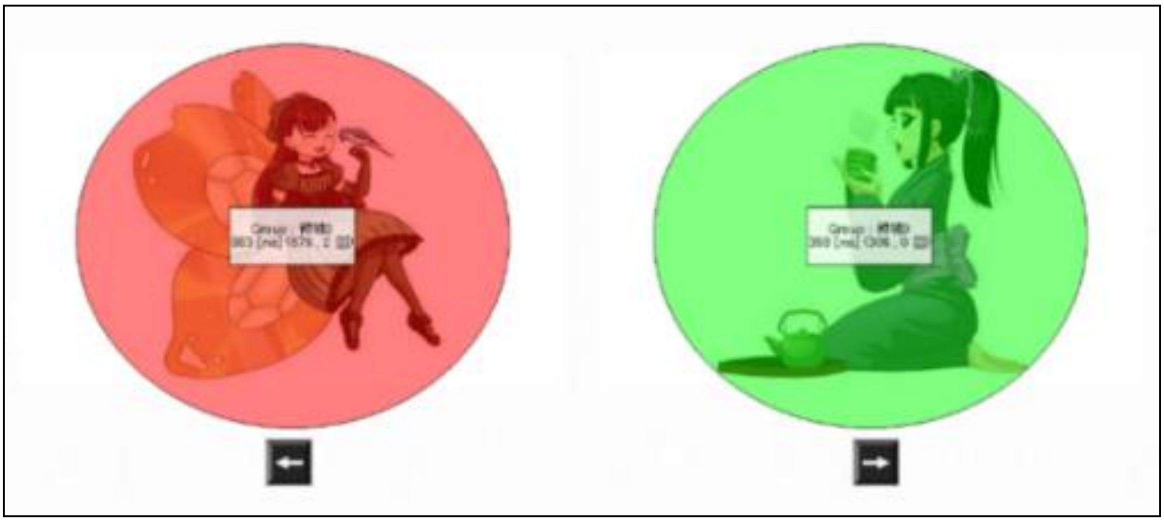


**Figure 3.7** Example of AOIs of two illustrations with identical shape and size showing areas included in analysis of eye tracking data

I analyzed the eye tracking data by employing six eye movement indexes, all of which I describe in the following sections.

#### 3.3.4.1 Total AOI duration (sum of durations of all eye positions inside AOI)

I analyzed the total AOI duration with two factors, the participant and illustration groups. The illustration groups include the highest kawaii score, the lowest kawaii score, the most selected kawaii illustrations, and the most selected favorite illustrations. I analyzed the total AOI duration among the illustration groups for both all participants and the grouped participants. Paired t-tests identified whether a statistically significant mean difference existed between the total AOI duration among four illustration groups. The result showed a significant difference in the total AOI duration between the illustrations with the highest and lowest kawaii scores ($p<0.05$) for females in their 20's. For the other illustration groups and participant groups, I found no significant differences in total duration. The result of the average total AOI duration is illustrated in Figure 3.8.

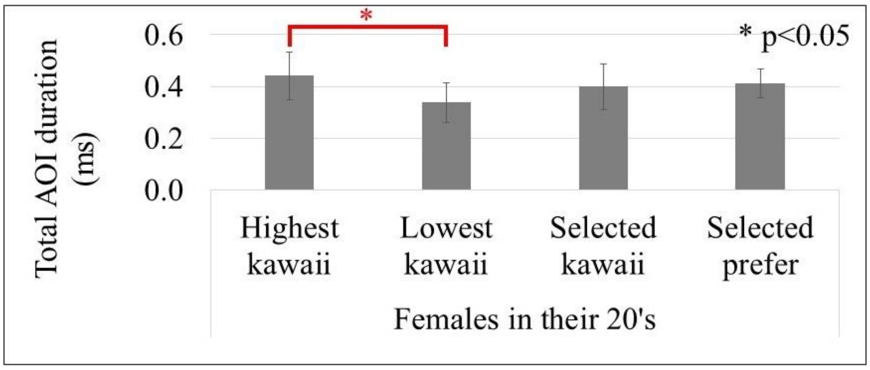



**Figure 3.8** Total AOI duration vs. illustration groups of females in their 20’s where highest kawaii refers to illustrations with highest kawaii scores, lowest kawaii refers to illustration with lowest kawaii scores, selected kawaii refers to illustrations selected as most kawaii, and selected prefer refers to illustrations chosen as favorites, of each participant

#### 3.3.4.2 Total number of fixations (sum of all fixations inside AOI)

I analyzed the total number of fixations with two factors: participant and illustration groups. I performed a statistical analysis with the same method as that for the total AOI duration. The result of all participants from the paired t-tests showed a significant difference in the total number of fixations between the highest and lowest kawaii scores ($p<0.05$) and between the most selected kawaii and lowest kawaii score ($p<0.05$) (Figure 3.9).

Furthermore, the result of the grouped participants from the paired t-tests showed a significant difference in the total number of fixations between the most selected kawaii and the lowest kawaii score ($p<0.05$) and between the most favorites and the lowest kawaii score ($p<0.05$) for females in their 20’s. For other groups of illustrations and participant groups, there were no significant differences in the total number of fixations. The result of the average total number of fixations is illustrated in Figure 3.10.

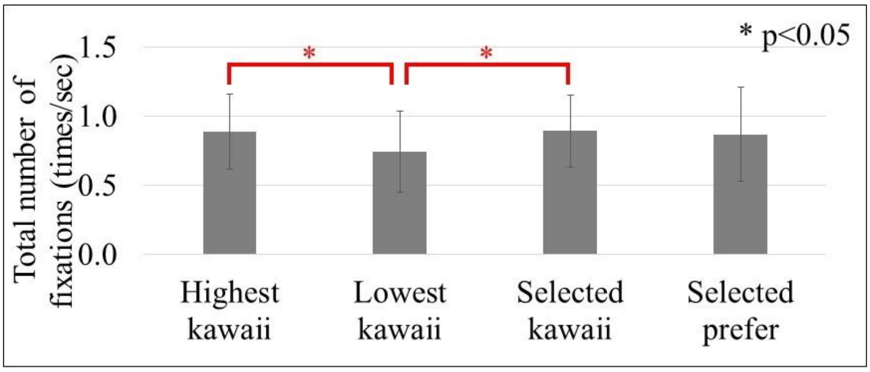



**Figure 3.9** Total number of fixations vs. illustration groups of all participants (details are identical as described in Figure 3.8)

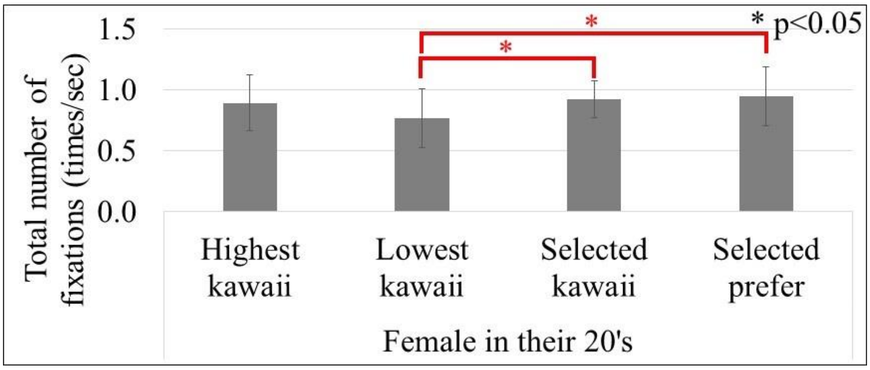



**Figure 3.10** Total number of fixations vs. illustration groups and participant groups of females in their 20’s (details are identical as described in Figure 3.8)

#### 3.3.4.3 Number of transitions between AOIs (sum of times that the eyes moved between AOIs for each pair of illustrations)

I counted the eye movement from one position in an AOI to another position in another AOI as a transition. For example shown in Figure 3.11, the number of transitions is 3 times as the eye positions move for 3 times between left and right AOIs.

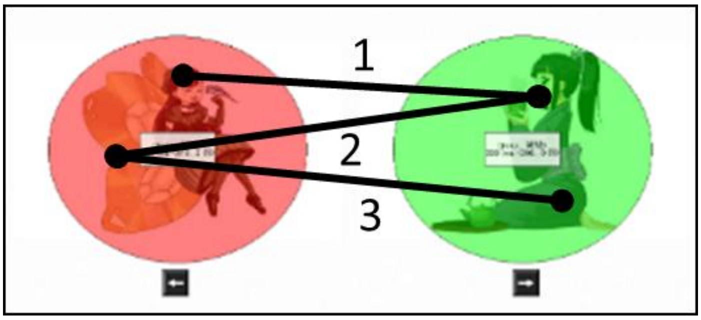



**Figure 3.11** Example of method to calculate number of transitions between AOIs

I analyzed the number of transitions between the two AOIs for all participants and each participant group. Since I considered the illustrations pair by pair, the difference of kawaii scores between each pair was calculated from the cumulative and questionnaire results that I used to analyze this eye tracking metric. A Pearson product-moment correlation determined the relationship between the number of transitions and the differences of the kawaii scores. A scatter plot between these two variables (Figure 3.12) shows a linear relationship with a negative correlation. The result shows a statistically significant ($R^2$=-0.125, p<0.01) negative correlation between the number of transitions and the differences of kawaii scores.

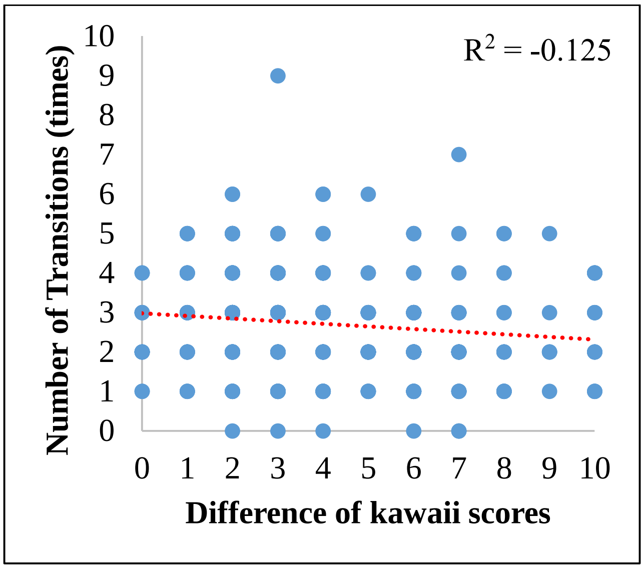



**Figure 3.12** Number of transitions between AOIs and differences of kawaii scores of all participants where red line shows negative linear relationship between these two variables

I also analyzed the number of transitions between AOIs for each participant group. The results showed similar tendencies as the result of all participants for both males in their 20's and females 65 or older. There were negative correlations between the number of transitions and the differences of kawaii scores with a statistical significance for males in their 20's (p<0.05) and females 65 or older (p<0.1). The result of the females in their 20's did not show a statistical difference for the correlation. However, it did have a similar tendency as in the other participant groups, where a negative linear relationship existed between the number of transitions and the differences of the kawaii scores.

#### 3.3.4.4 Number of matchings between last-eye-position illustrations and selected illustrations

I collected and analyzed the matched and unmatched numbers for each pair of illustrations between the last-eye-position illustrations and the selected illustration from the cumulative and questionnaire results (Figure 3.13). Paired t-tests determined whether a statistically significant mean difference existed between the number of matched and unmatched selections for each participant group. The result from each participant group showed a significant difference in the number of matchings between the last-eye-position and the selected illustrations (p<0.01) (Figure 3.14).

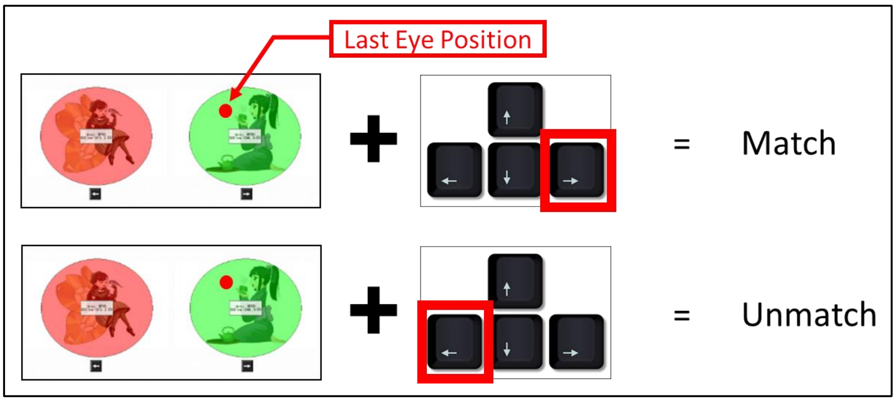



**Figure 3.13** Example of method to calculate number of matchings between last-eye-position illustrations and selected illustrations

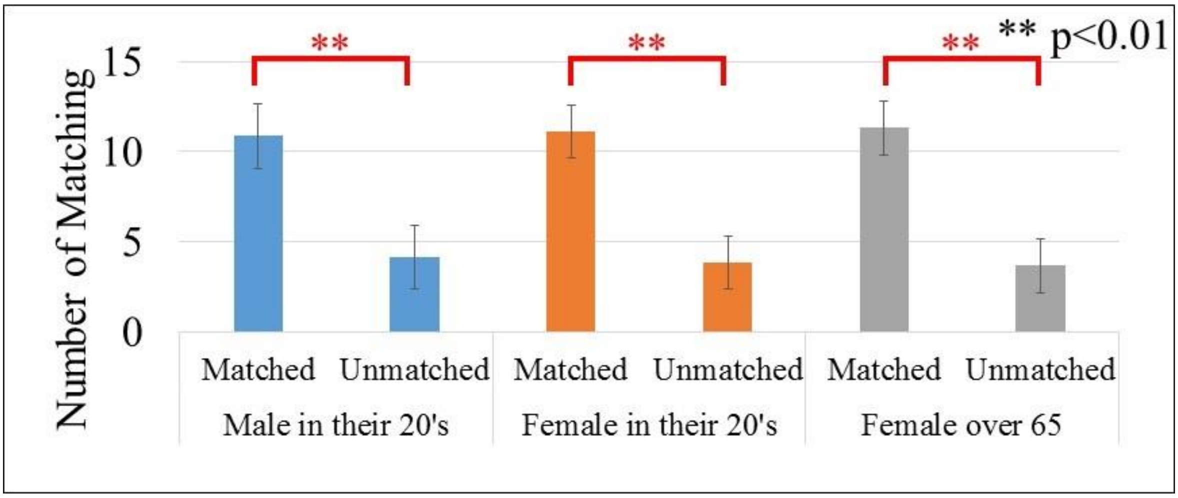



**Figure 3.14** Number of matchings between last-eye-position and selected illustration of first 15 illustration pairs for each participant

#### 3.3.4.5 Total duration of decision (time from occurrence of pair of illustrations to selection by arrow keys)

I compared the total duration to identify the differences of the kawaii scores for each participant group. A Pearson product-moment correlation determined the relationship between these two variables. A scatter plot for the female participants in their 20's (Figure 3.15) shows a statistically significant ($R^2$ = -0.206, $p<0.05$) linear relationship with a negative correlation between the total duration of decision and the differences of the kawaii scores for females in their 20's. The results for males in their 20's and females 65 or older did not show a statistical difference for the correlation.

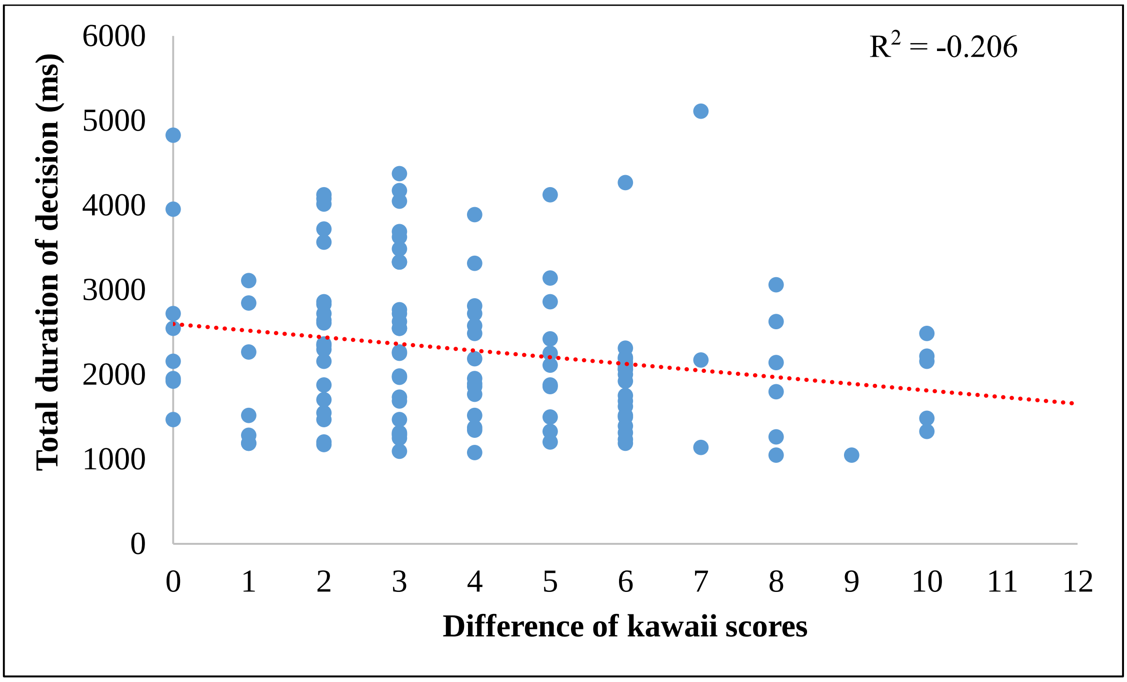



**Figure 3.15** Total duration of decision and difference of kawaii scores for females in their 20's where red line shows negative linear relationship between these two variables

#### 3.3.4.6 Number of initial eye positions on each focused area (sum of eye positions that were first inside each focused area in AOI)

To collect the number of initial eye positions, I defined the focused areas that participants tended to look on their first glance. Since all of the illustrations were composed of human structure, I categorized the focused areas into three groups: head, body, and others (Figure 3.16).

I measured and calculated the head-to-body ratios for all the illustrations using head and body heights (Figure 3.17). I also listed the objects for other areas that included the objects that surrounded the head and body. The structure information of the six illustrations is shown in Table 3.5. The head-to-body ratio showed the varieties of head and body sizes. Moreover, there were various objects in the other areas for all six illustrations.

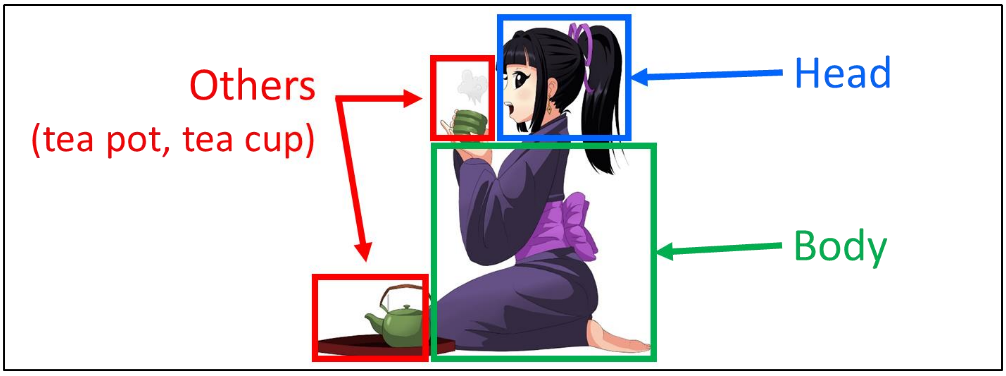



**Figure 3.16** Example of illustration divided into three focused areas (head, body, and other areas)

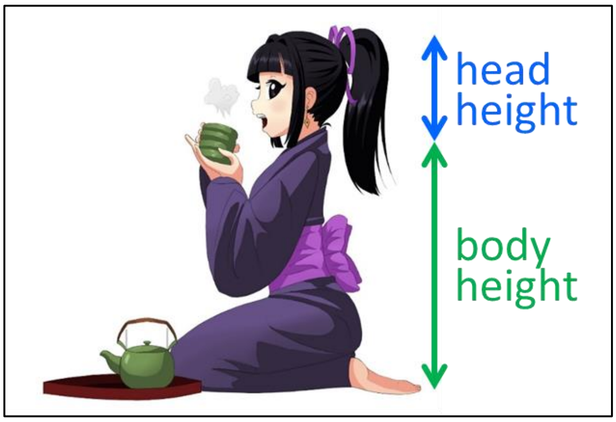



**Figure 3.17** Example of illustration showing method to measure head and body heights

**Table 3.5** Structure information of six illustrations

| Illustration No. | Head Height (pixels) | Body Height (pixels) | Head-to-body Ratio | Surrounding objects |
|---|---|---|---|---|
| 1 | 155 | 187 | 0.829 | Stars |
| 2 | 74 | 209 | 0.354 | Wings, bird |
| 3 | 88 | 207 | 0.425 | Bear, pillow |
| 4 | 105 | 244 | 0.430 | Tea pot, tea cup |
| 5 | 119 | 199 | 0.598 | Rope |
| 6 | 155 | 180 | 0.861 | Luggage, lollipop |

I analyzed the number of initial eye positions using a two-factor ANOVA between the focused areas and the participant groups for each illustration. The result showed significant differences ($p<0.01$) among the focused areas for all the illustrations. I performed a low-level analysis using the percentage of the number of first eye positions shown in Figure 3.18. The head area tended to have the highest percentage of initial eye positions. In addition, the graph showed a tendency between genders where the numbers of first eye positions on body areas were larger in the female participants than in the male participants.

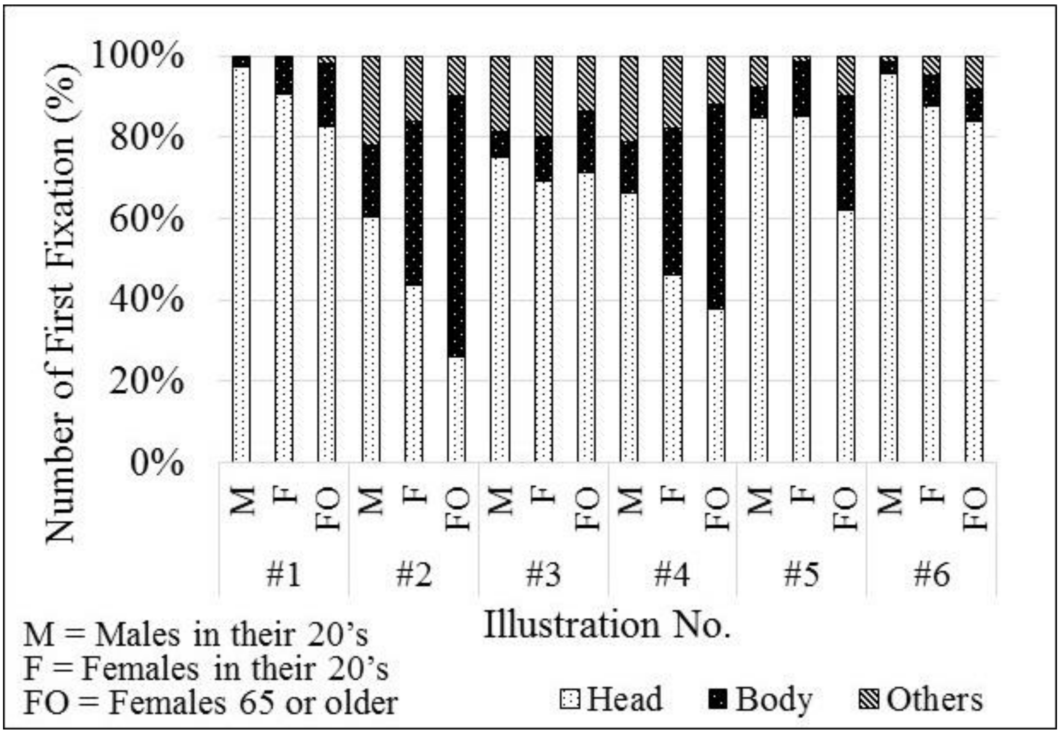



**Figure 3.18** Percentage of first fixations for all participant and illustration groups. Each bar graph shows percentage of first fixations among head, body, and other areas of each illustration.

## 3.4 Discussion

Analysis of rankings shows the similarity of the first and last ranking tendencies between the results of the cumulative kawaii scores and the more kawaii illustrations from the questionnaire results. In addition, the first ranking tendencies of the selected favorite illustrations were similar for all the participant groups.

The eye tracking analysis included six eye tracking indexes and the following results:

- **Total AOI duration** of females in their 20's showed significant differences between the illustrations with the highest and lowest kawaii scores. They tended to look longer at the kawaii illustrations, while the two other participant groups showed average attention to all the illustration groups.

- **Total number of fixations** of all participants showed significant differences between the illustrations with the highest kawaii scores and the selected kawaii illustrations versus illustrations with the lowest kawaii scores. The illustrations with the highest kawaii scores and the selected kawaii illustrations had more fixations.

- **Total number of fixations** of females in their 20's showed significant differences between selected kawaii illustrations and the illustrations with the lowest kawaii scores, and between their selected favorite illustrations and the illustrations with the lowest kawaii scores. They tended to look more frequently at their more kawaii selections and favorite illustrations.

- **Number of transitions between AOIs** versus the differences of kawaii scores had a significantly negative correlation for all participants, males in their 20's, and females 65 or older. For females in their 20's, the result also showed negative tendencies that resembles the other two participant groups.

- **Number of matchings between the last-eye-position illustrations and the selected illustration** showed a significant difference for the three participant groups. The larger number of matchings showed that the participants tended to take one final look at the illustrations they selected.

- **Total duration of decision** versus the differences of the kawaii scores had a significantly negative correlation for females in their 20's, who tended to take a longer time to decide if the kawaiiness of the pairs of illustrations were similar.

- **Number of first fixations for each focused area** showed a significant difference. The illustrations had various head and body sizes. All three participant groups looked more at the head areas than the other areas. Even though the head might be large or small, it attracted the most initial attention, showing that the participants looked first at the heads regardless of their sizes. The result of participants who looked first at the head area most corresponds to the result of question (3) where the participants selected illustrations based on eye size, face shape, and hairstyle. In another tendency, the females also first looked at the body and other areas in addition to the head than males, suggesting interest in other areas in addition to the head. These results show that there is possibility to clarify kawaii parts by defining AOIs to various parts and analyzing this eye movement index.

From our analyzed results, females in their 20's tended to look longer and more frequently at more kawaii illustrations, suggesting that they have the strongest interest in kawaii. All participants repeatedly compared the illustrations before selecting when the kawaiiness of two illustrations were similar. Finally, our results also revealed that females tend to judge kawaiiness based on the complete atmosphere while males focused on faces.

The correlation results of two eye movement indexes (number of transitions between AOIs and total duration of decision) were too weak to conclude the relationship between these eye movement indexes and kawaii feelings. However, these indexes were still candidates to measure kawaii feelings. If number of participants is increased, there is possibility that the result is more significant.

As a result, I clarified the relationship between kawaii feelings and eye movement indexes and identified two new indexes: (1) number of transitions between AOIs and (2) number of matchings between last-eye-position illustrations and selected illustrations. In addition, there is possibility that other indexes can be identified by using other analysis methods. For example, if eye movements are classified into longer or shorter fixation duration, then the relationship between classification result and kawaii scores can be analyzed.

For the application of these indexes, not only one specific index, but the combination of various indexes should be useful for measuring kawaii feelings. If more number of indexes can be clarified, they might indicate more information for kawaii feelings.

During this experiment, I faced some problems that might complicate collecting and analyzing eye tracking data. The problems will be used to improve the comparison system and experimental setup in further study.

- Identical illustrations were displayed at the same position during two consecutive pairs.
- The participants did not have default eye position before they started evaluating the illustrations.
- Some participants used a mouse instead of a keyboard during the selection of illustrations which might cause slower eye movements and increase cognitive workload for the hand-eye interactions.
- Ceiling light and sunlight affected to devices which failed to calibrate or track eye movements.

## 3.5 Conclusion

This chapter presents my study of kawaii feelings using eye tracking. I experimentally used a comparison system with an eye tracking system and used the cumulative results, the questionnaire results, and the recorded eye tracking data for analysis. I clarified the relationship between kawaii feelings and eye movement indexes.

Females in their 20's tended to look longer and more frequently at more kawaii and their favorite illustrations. All participants tended to take longer to compare pairs whose kawaiiness was similar. The participants all tended to take one last look at the illustration they selected. Finally, all participants tended to focus on the head area when they first looked at the illustrations.

I clarified the relationship between kawaii feelings and eye movement indexes which indicated that eye tracking was an effective method to evaluate kawaii feelings. Therefore, I employed the eye movement indexes related to kawaii feelings to next researches. The detail will be described in Chapter 5 and Chapter 6.

# Chapter 4

# Evaluation of Spoon Designs based on Kawaiiness between Genders and Nationalities

## 4.1 Background

In previous chapter, I performed experiment to evaluate kawaii feelings among genders and generations of Japanese participants. However, kawaii products are increasingly popular not only in Japan but also worldwide, especially in such Asian countries as Thailand [67], Singapore [68], and Taiwan [69]. Therefore, a focus on studying kawaii feelings was not limited to only Japanese participants.

Thailand is one country that has been strongly influenced by kawaii culture for several years. Research [67] pointed out that Thailand has been strongly influenced by kawaii culture by demonstrating that kawaii is expressed through various forms of daily products such as clothing and cosmetics. These kawaii products have been embraced by Thai people, especially young females. Moreover, the word “kawaii” itself is transliterated and frequently used in daily conversation by both Thai males and females. However, various factors might impact the shifting of kawaii impressions away from the idea’s original connotations. Thus, it remains unclear whether the impressions of kawaii perceived by Thai people actually resemble those of Japanese people. Revealing the similarities and the differences between such impressions in Japan and Thailand will be useful for the design of future kawaii products that serve the desires of customers in both countries. Therefore, this research focused not only on the study of kawaii feelings but also its similarities and differences between Japanese and Thai people.

## 4.2 Preparation

### 4.2.1 Collection of Spoon Designs

Female students at Tokyo Woman’s Christian University participated in the design of kawaii spoons. I used a layout of spoon design provided by Aoyoshi Co., Ltd. [70], a manufacturer of household goods. This layout consists of top and side views (Figure 2.2). The participants were asked to design a kawaii spoon by drawing on the given layout. I collected 182 spoon designs.

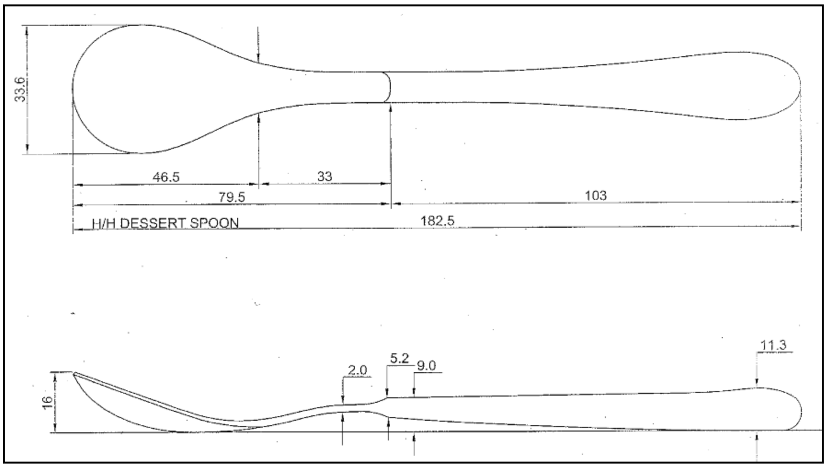



**Figure 4.1** Layout of spoon design (Aoyoshi Co., Ltd.)

### 4.2.2 Preparation of Spoon Designs

I prepared spoon designs to select the best examples for our experiment. In this step, I considered only the top-view spoon designs because some side-view spoon designs were difficult to draw which could misrepresent the actual intention of the designs. Also, based on the practicality of actually using the spoon, I only considered the designs of the handles.

I excluded 20 out of 182 spoon designs based on the following criteria:

- Three designs with cartoon characters: This group of designs was excluded to eliminate potential preference bias caused by the cartoon characters.
- 17 designs with non-surfaced decorations: This group included designs with items that were placed over the spoon's surface. They were excluded due to such practicality issues as difficulty in using or cleaning.

I divided the remaining 162 spoon designs into groups based on the appearances or the shapes of the objects on the designs, such as flowers, hearts, smileys, stars, cats, etc. I counted the number of designs of each group and selected spoon designs from the three shape groups with highest numbers of designs: the flower group (37 designs), the heart group (13 designs), and the smiley group (13 designs). I selected them as candidates for the experiment and excluded the other 99 designs.

## 4.3 Preliminary Experiment

I obtained 63 designs and divided them into three shape groups. However, the number of designs in the flower group was much larger than the other two groups. Therefore, I performed a preliminary experiment to reduce the number of flower designs.

### 4.3.1 Participants

I recruited three female participants of different nationalities (Japanese, Thai, and Brazilian).

### 4.3.2 Preliminary Experimental Procedure

I created a questionnaire using Google Form. The participants answered it online using their own PCs. The questionnaire started with an instruction part that described how to evaluate the spoon designs. Then it advanced to the question parts, which included 37 questions, each of which showed spoon design image, and asked "How kawaii is the spoon design?" (Figure 4.2). The participants rated the designs using 4-point rating scales: 0 (not at all), 1 (low), 2 (moderate), and 3 (high). After rating all 37 spoon designs, the participants clicked the "submit" button to save the questionnaire results in the system.

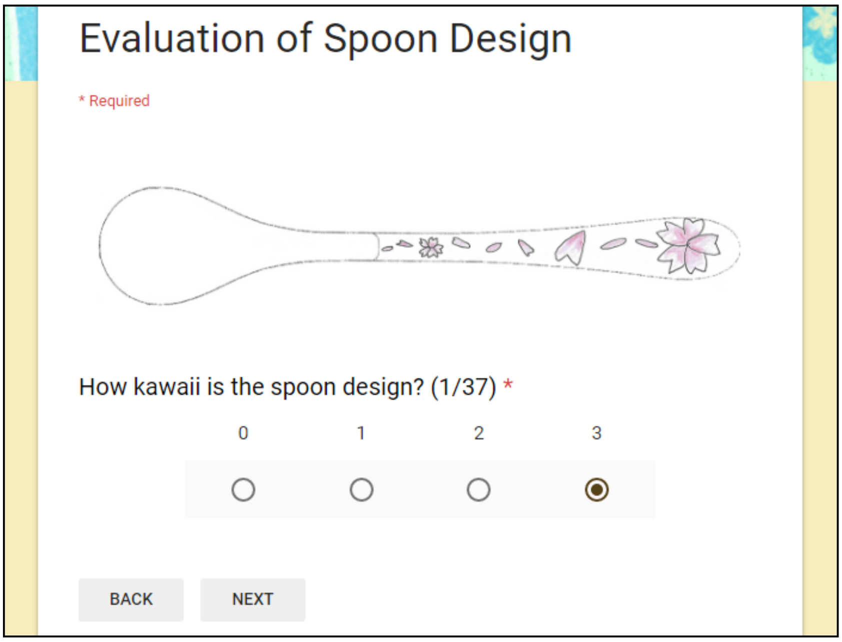



**Figure 4.2** Screenshot of questionnaire in preliminary experiment

### 4.3.3 Preliminary Experimental Results

Based on the questionnaire results, I summed up the ratings for each spoon design from the ratings by all three participants and selected 13 highest rated designs as more kawaii. These selected designs and the other designs in the heart and smiley groups are used in the experiment described in the next section.

## 4.4 Experiment on Comparison of Spoon Designs

### 4.4.1 Candidates of Spoon Designs

From the previous steps, I obtained 39 spoon designs and divided them into three shape groups: 13 flower designs, 13 heart designs, and 13 smiley designs. However, since these designs were originally hand-drawn by students with different drawing ability, all 39 designs were graphically redrawn by a professional artist to remove any potential bias in different drawing quality that might affect the comparison results (Figure 4.3). Then I used them in the experiment.

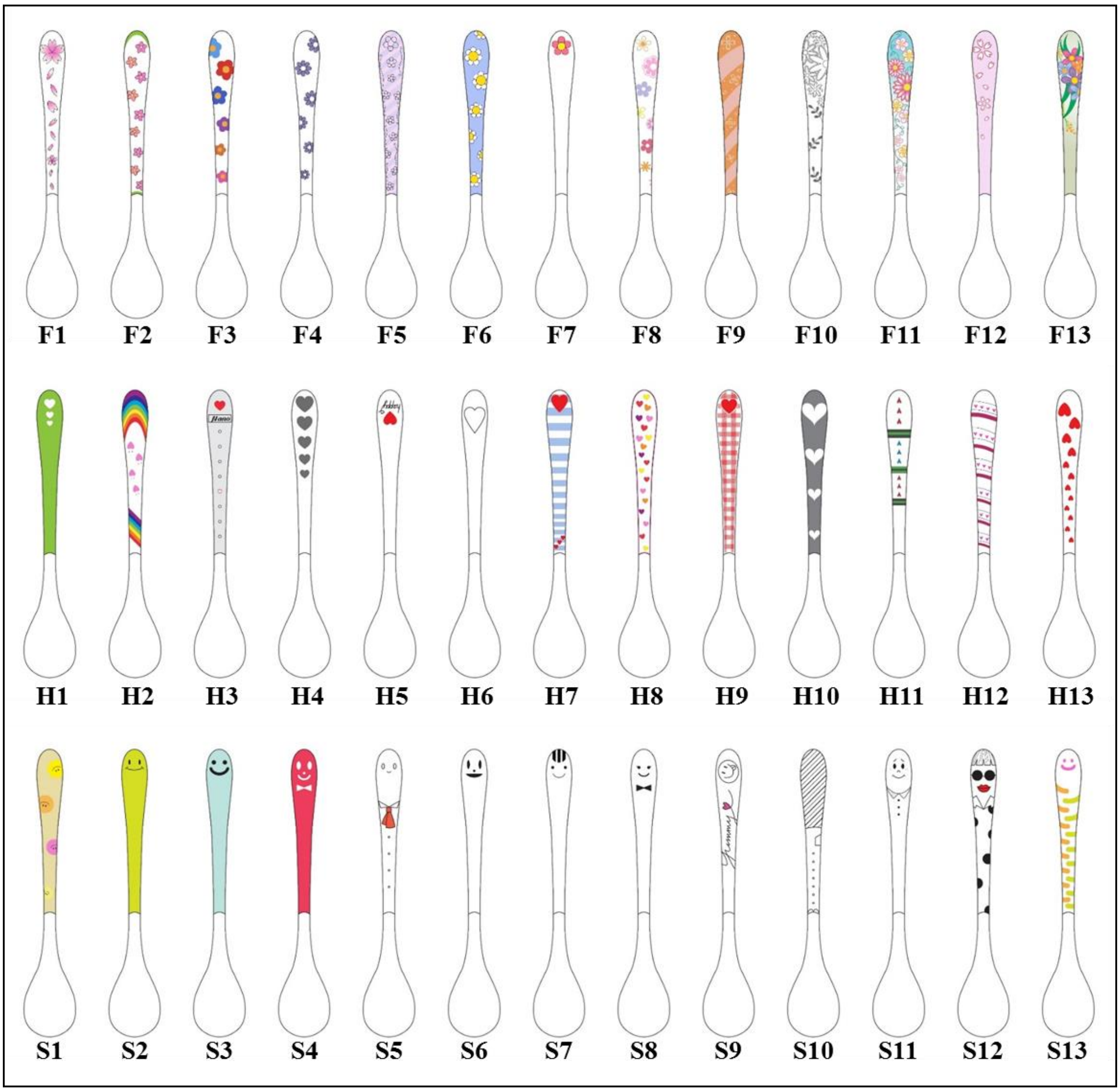



**Figure 4.3** Candidates of spoon designs

### 4.4.2 Comparison System

I modified a spoon comparison system from previous schemes that evaluated kawaii ribbons [63] and kawaii illustrations (Chapter 3). This system collected the comparison results of kawaii spoon designs. As visual stimuli, the system used 39 graphical spoon designs that were displayed in pairs on a PC monitor (Figure 4.4).

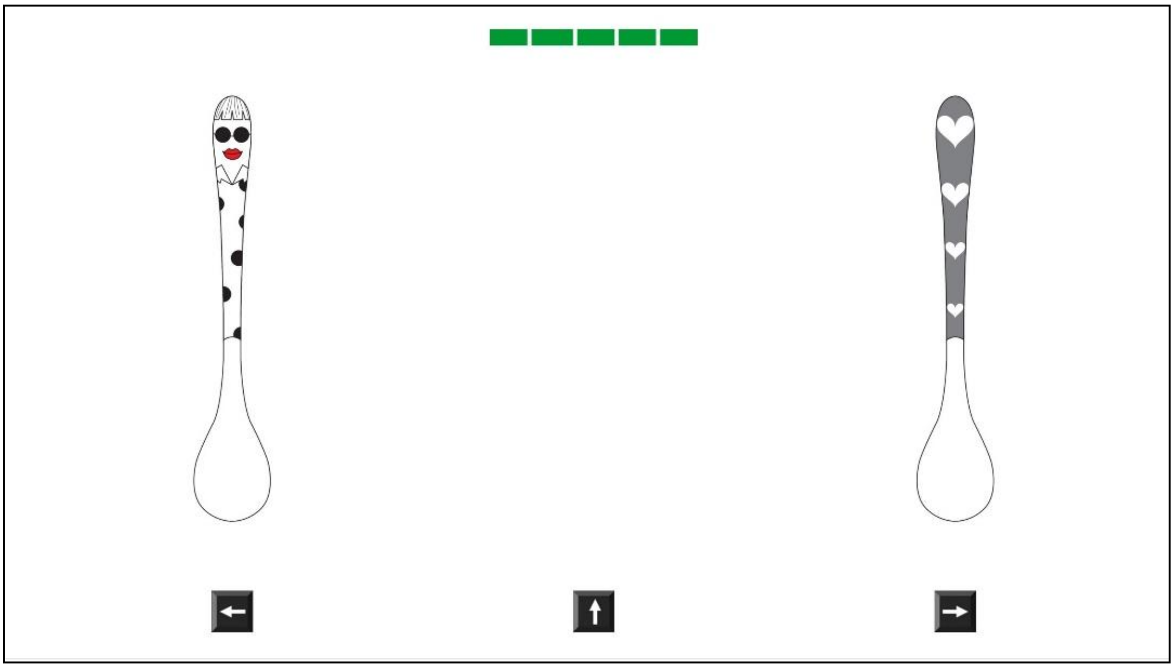


**Figure 4.4** Screenshot of spoon comparison system displaying two spoon designs

The system's structure is described as follows:

4. Top page: explanation of comparison method;
5. Consent form: brief explanation about the experiment and permission to use their data;
6. Selection of participant's gender and nationality;
7. Instruction of method to answer the comparison result of spoon designs;
8. Spoon design comparison: pairs of spoon designs were displayed with a countdown timer for five seconds. Then the system asked participants to select from three comparison results (more, less, or equally kawaii) using the keyboard's arrow keys.
9. Last page: the system explained that the comparison was finished and saved the result in a database.

The comparison method used in the system was a quicksort algorithm (Figure 4.5). Since the number of spoon designs for comparison was large, this method reduced the comparison number and duration, but all of the spoon designs could still be evaluated. The following steps explain our method:

1. A spoon design was randomly selected and shown on the left side as a pivot (P).
2. The other spoon design (Q) was selected and shown on the right side.
3. Participants compared a pair of spoon designs: P vs. Q.
4. Participants answered using the keyboard's arrow key. Then Q was sorted into one of the following groups based on the answers:
5. If Q was deemed more kawaii than P, then it was sorted into the "more kawaii" group.
6. If Q was deemed less kawaii than P, then it was sorted into the "less kawaii" group.
7. If P and Q were deemed equally kawaii, then it was sorted into the "equally kawaii" group.
8. The system repeated Steps 2 to 4 until all the spoon designs were compared.
9. Spoon designs were divided into three groups: more kawaii (A), less kawaii (B), and equally kawaii (C). Spoon designs in the "less kawaii" group were compared again through Steps 1 to 5, and then followed by those in the "more kawaii" groups. For spoon designs in the "equally kawaii" group, the system stopped the comparison.
10. Step 6 was repeated until the "more kawaii" and "less kawaii" groups contained only one spoon design which meant there were no other spoon designs in the same group for comparison.

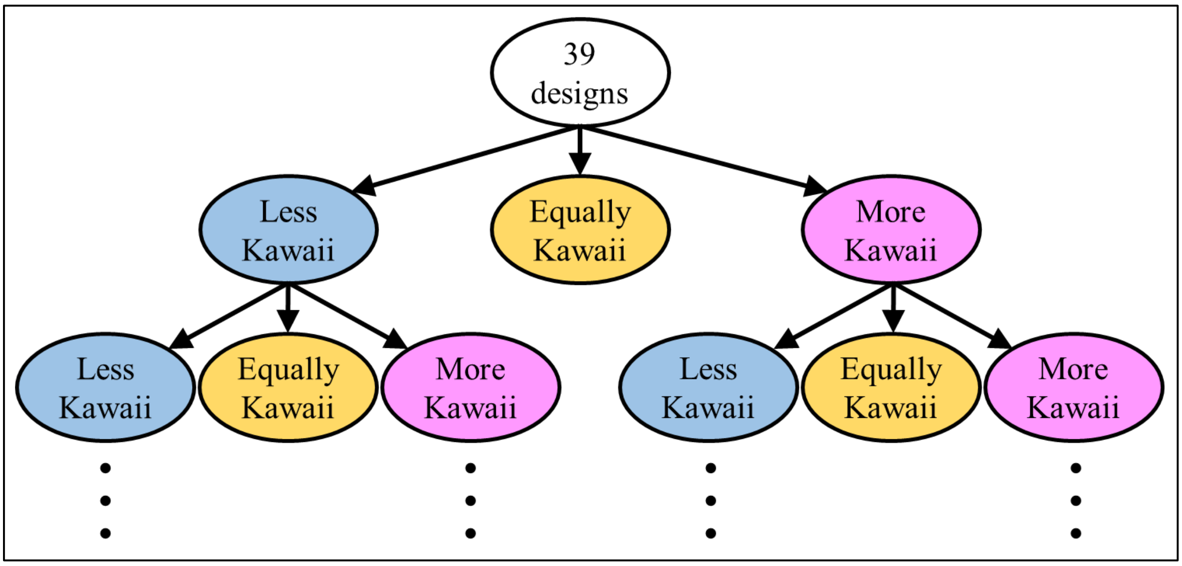



**Figure 4.5** Tree structure of quicksort-based comparison

### 4.4.3 Experimental Setup and Procedure

The comparison system was displayed on a web browser with a 13-inch monitor and resolution of 3200x1800 pixels. The following are the experimental procedures:

1. Participants sat on a chair in front of a PC.
2. The experimenter showed the spoon comparison system.
3. Participants read the explanation and instruction on the display.
4. Participants submitted a consent form and agreed to cooperate in the experiment.
5. Participants compared the pairs of spoon designs from those shown on the PC display.
6. Participants input their answers about the comparison results.

## 4.5 Experimental Results

### 4.5.1 Participants

The experiment was performed with 40 volunteers, all of whom were university students in their 20's. They were divided into four groups by gender and nationality: ten Thai males, ten Thai females, ten Japanese males, and ten Japanese females.

### 4.5.2 Comparison Results

From the comparison results of each participant, I sorted all 39 spoon designs and ranked them using the method described below.

With the sorting result as a tree structure, the spoon designs in the bottom "more kawaii" group were ranked as the most kawaii or the 1st rank. The spoon designs in the bottom "less kawaii" group were ranked as the least kawaii. Two or more spoon designs in the "equally kawaii" group had the same rank.

From the rankings, I calculated the scores of all the spoon designs. The score of the 1st rank was 39. If the rank was worse, the score was lowered. I used the scores to analyze the comparisons of the spoon designs and to describe the analyzed results in the following sections. Example of the method to rank and score the spoon designs is shown in Figure 4.6.

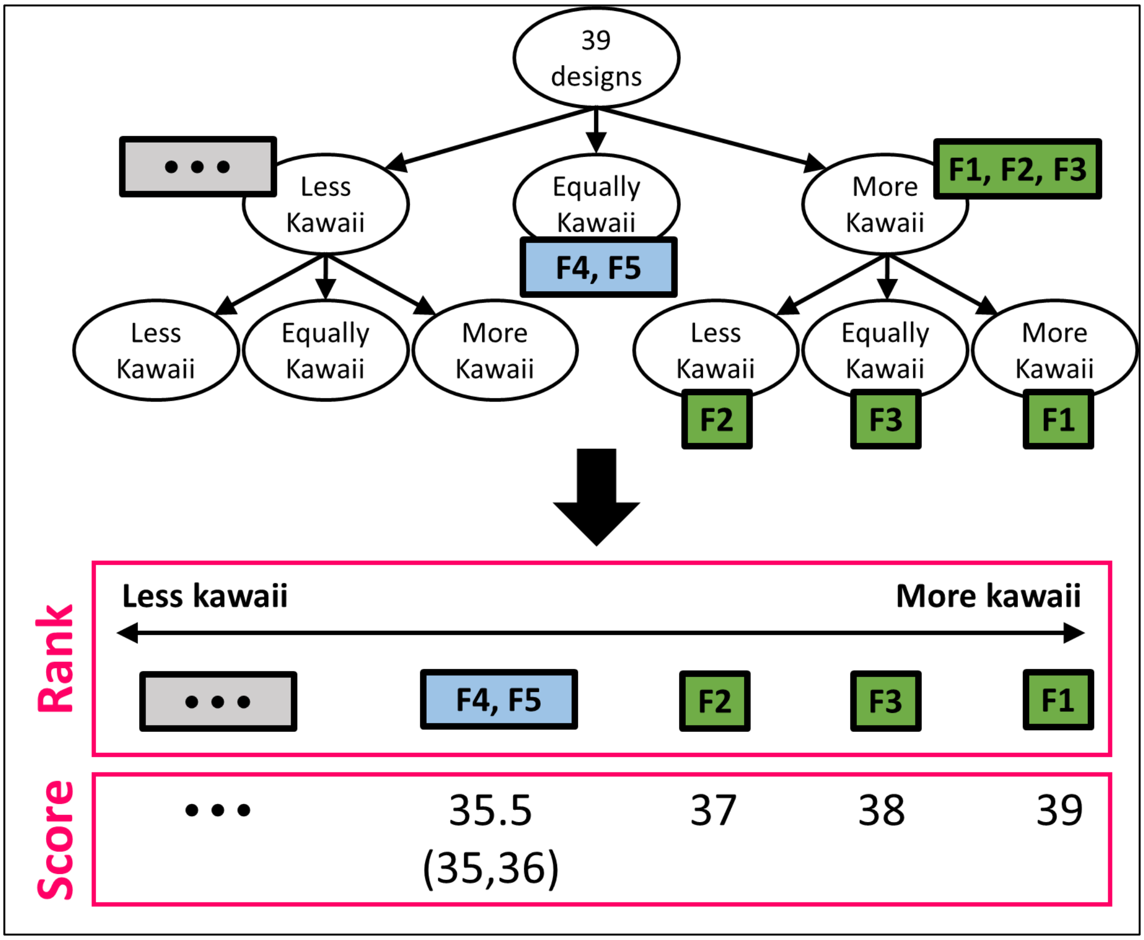



**Figure 4.6** Example of the method to rank and score the spoon designs

#### 4.5.2.1 Comparison among Shapes, Genders, and Nationalities

I performed 3-factor ANOVA to examine the effect of shape, gender, and nationality on the scores of spoon designs. The results were as follows:

- There was a significant main effect of shape ($p<0.01$).
- There was a significant 2-factor interaction effect between shape and nationality ($p<0.01$).
- There was a significant 3-factor interaction effect among shape, gender, and nationality ($p<0.05$).

For each shape, Tukey post hoc tests between participant groups showed significant differences in average scores between Japanese males and females for flower and smiley groups ($p<0.05$) (Figure 4.7).

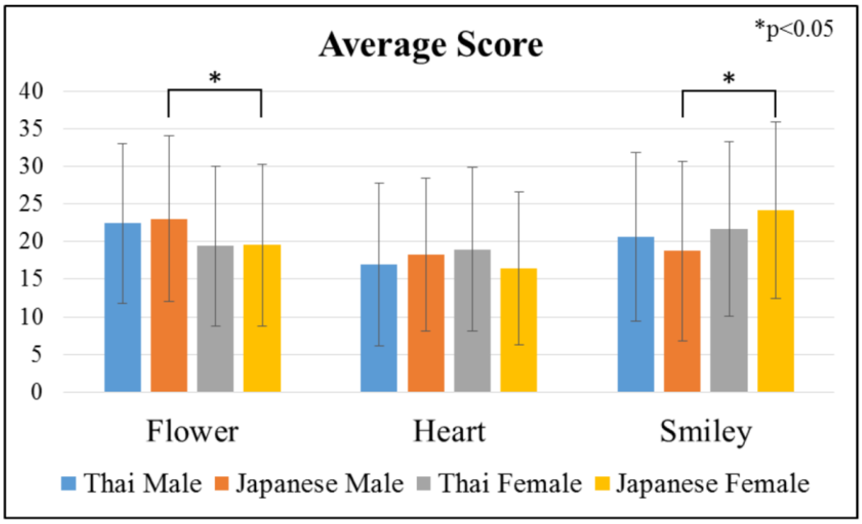



**Figure 4.7** Comparison of average scores among participant groups for each shape of spoon designs

For each participant group, Tukey post hoc tests between shapes showed significant differences in average scores (Figure 4.8) as follows:

- Thai males: flower and heart ($p<0.01$), smiley and heart ($p<0.05$)
- Japanese males: flower and heart ($p<0.01$), flower and smiley ($p<0.01$)
- Japanese females: flower and smiley ($p<0.01$), smiley and heart ($p<0.05$)
- For Thai females, there were no significant differences

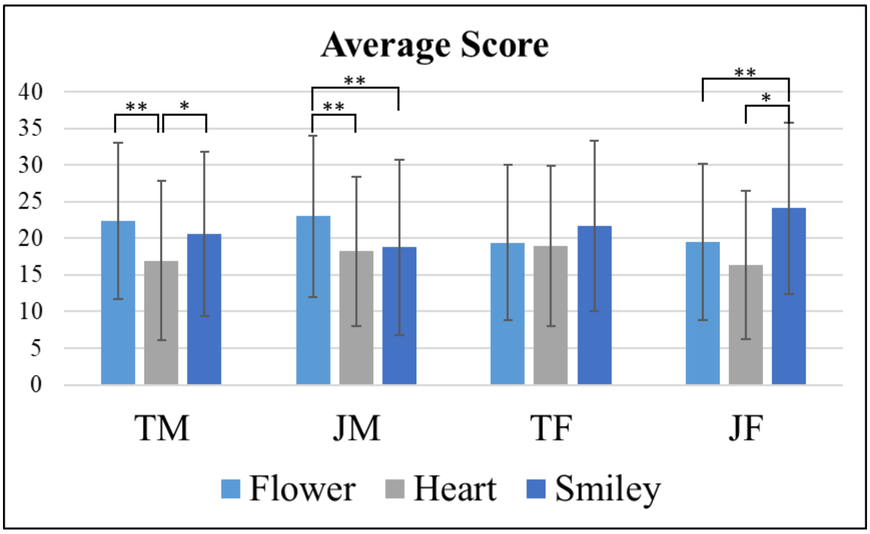



**Figure 4.8** Comparison of average scores among shapes of spoon designs for each participant groups

These results indicate that each participant groups considered the following shapes as more kawaii spoon designs.

- Thai males preferred flower and smiley shapes.
- Japanese males preferred flower shape.
- Japanese females preferred smiley shape.
- Thai females preferred all shapes equally.

#### 4.5.2.2 Comparison of Individual Spoon Designs

I performed 1-factor ANOVA of the average scores among 39 spoon designs. The result showed a significant main effect of spoon designs ($p<0.01$). Next, I performed Tukey post hoc tests to compare the average scores of each spoon design between the pairs of four participant groups. Figure 4.9 shows the average scores of the 39 spoon designs of four participant groups.

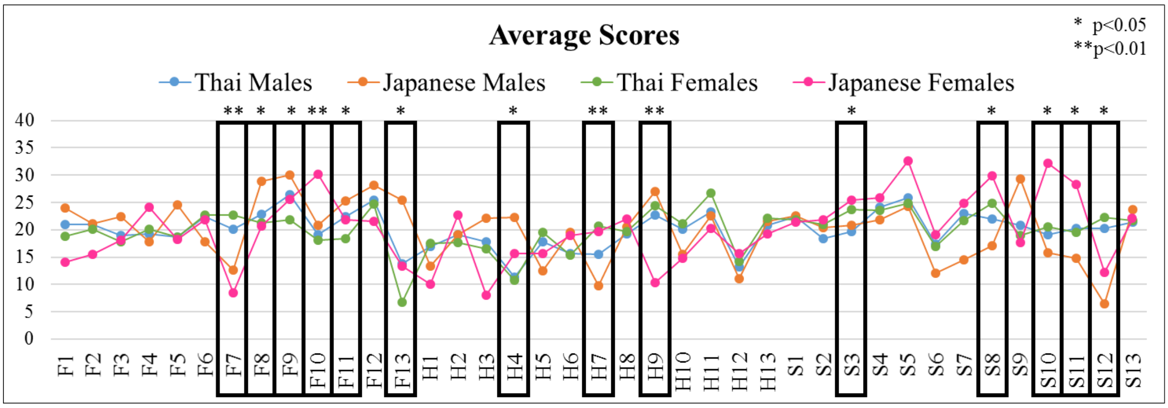



**Figure 4.9** Average scores of 39 spoon designs among four participant groups. The spoon designs with bracket indicated that there was significant difference in score.

As the results, there were 25 spoon designs which had no statistically significant differences in average scores between any pairs of the four participant groups. Each of these spoon designs had similar ranking tendency for all participants. On the other hands, there were 14 spoon designs had significant differences in average scores between pairs of participant groups as follows:

- Thai males vs. Japanese males: H4 and S12
- Thai females vs. Japanese females: F7, F10, and H9
- Thai males vs. Thai females: F9, F11, F13, H7, and S3
- Japanese males vs. Japanese females: F8, H9, S8, S10, and S11

The spoon designs with different average scores can be used to suggest more kawaii spoon designs for specific participant groups. For example, F8 and H9 were more kawaii for Japanese males, while S8, S10, and S11 were more kawaii for Japanese females (Figure 4.10).

Finally, I compared the average scores among 39 spoon designs for all participant groups. The spoon designs which had 10 highest average scores (Figure 4.11) can be suggested as kawaii spoon designs in general.

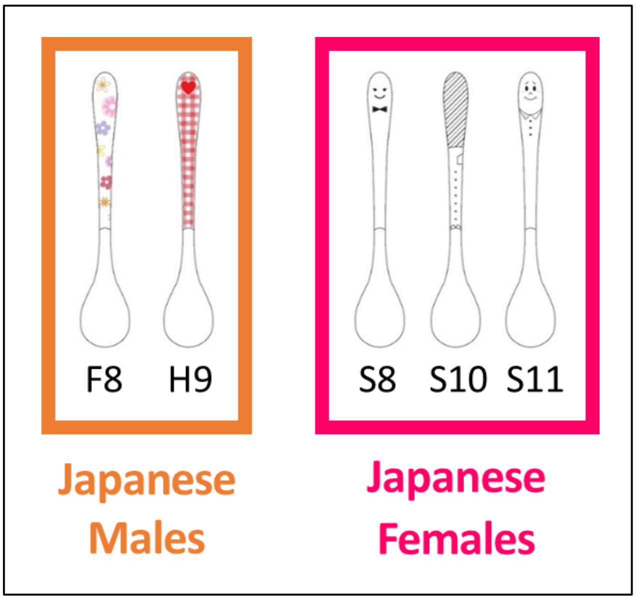



**Figure 4.10** More kawaii spoon designs for Japanese males (left) and females (right)

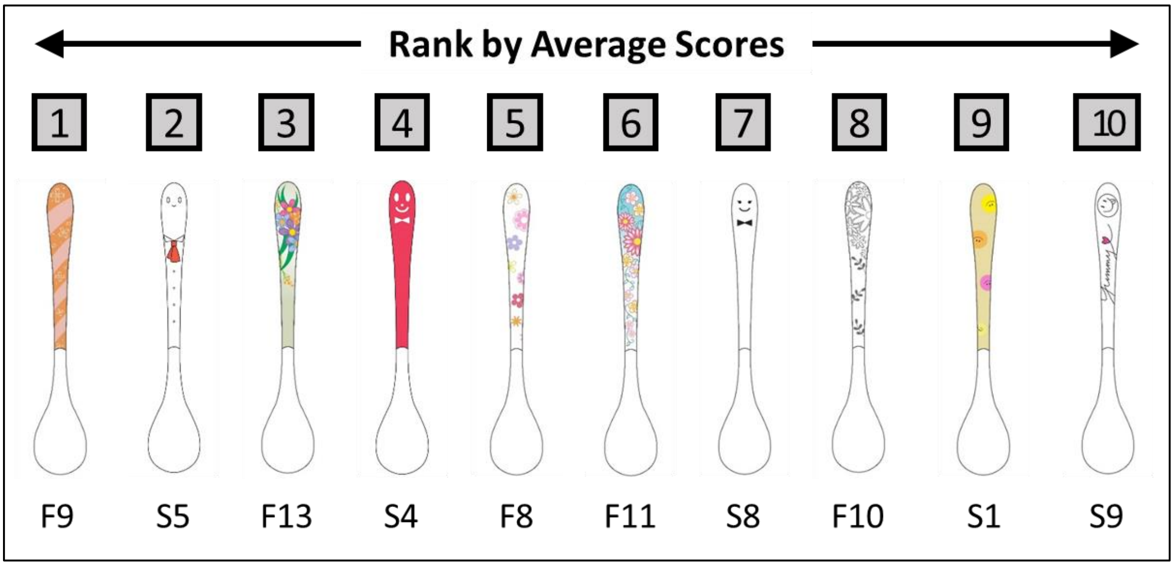



**Figure 4.11** Top 10 kawaii spoon designs in general ranked by average scores of all participants

#### 4.5.2.3 Correlation Analysis

Since I found the similarities and differences of average scores among the four participant groups, I performed further statistical analysis to clarify the correlations between the groups. I performed a correlation analysis of the average scores of the 39 spoon designs among the four participant groups using Spearman's rank-order correlation. Spearman's correlation coefficient ($r_S$) measures the strength and the direction of the monotonic relationships between two ranked variables. The $r_S$ ranges from -1 to +1, where -1 indicates a perfect negative association of ranks, +1 indicates a perfect positive association of ranks, and 0 indicates no association of ranks.

I compared the scores between four pairs of participant groups to clarify the similarities and differences between genders and nationalities. The $r_S$ value of the four comparison are shown in Table 4.1.

**Table 4.1** Comparison results between participant groups by Spearman's rank-order correlation

| | | Thai | | Japanese | |
|---|---|---|---|---|---|
| | | Male | Female | Male | Female |
| Thai | Male | | 0.329* | 0.649** | 0.294 |
| | Female | | | 0.104 | 0.342* |
| Japanese | Male | | | | 0.051 |
| | Female | | | | |

** Correlation is significant at 0.01 level (2-tailed).
* Correlation is significant at 0.05 level (2-tailed).

For the comparison between genders, I compared the $r_S$ of the Thai vs. Japanese males ($r_S$=.649, $p<0.01$) and the Thai vs. Japanese females ($r_S$=.342, $p<0.05$). The $r_S$ of the males was higher, which indicated stronger correlation between males than females.

For the comparison between nationalities, I compared the $r_S$ of the Thai males vs. females ($r_S$=.329, $p<0.01$) and the Japanese males vs. females ($r_S$=.051). The $r_S$ of the Thais was higher, which indicates stronger correlation between Thais than Japanese.

From the correlation analysis results, Thai males vs. Japanese males had a strong correlation, which indicates that they had a similar ranking tendency. These combinations had moderate correlations: Thai females vs. Japanese females, Thai males vs. Thai females, and Thai males vs. Japanese females. The combinations of Thai females vs. Japanese males and Japanese males vs. Japanese females had very weak or no correlations.

These results indicate that the tendencies of kawaii spoon designs between Thai and Japanese males are similar, while those between Japanese males and females are different.

## 4.6 Discussion

From the comparison of among shapes, genders, and nationalities, I obtained the following findings:

- For the preferences of kawaii spoon designs:
    - Japanese males tended to prefer flower designs.
    - Japanese females tended to prefer smiley designs.
    - Thai males tended to prefer flower and smiley designs.
    - Thai females tended to equally prefer flower, heart, and smiley.
- The correlation between Thai and Japanese males was the highest indicating that they had similar preferences for kawaii spoon designs. The correlation between Japanese males and females was very low, indicating that they had very different tendencies for kawaii spoon designs.

From the comparison of individual spoon designs, I identified the following similarities and differences in the average scores.

- More than half of spoon designs had no differences in average scores for all participant groups indicating that they were candidates of kawaii spoon designs for all participant groups.
- The results of top 10 spoon designs can be suggested as candidates of kawaii spoon designs in general for spoon manufacturers.
- Some spoon designs with higher average scores in some participant groups are strongly recommended for specific participant group.

Even though I can suggest the design idea, the suggestion had limitation to apply because it only showed the candidates of spoon designs but their attributes were not clarified yet. Therefore, further analysis was necessary to clarify the attributes and give more general suggestion to design kawaii spoons.

## 4.7 Conclusion

I compared 39 spoon designs based on kawaiiness between genders and nationalities. I developed a spoon comparison system and experimentally collected comparison results from Japanese and Thai participants, which were used for model construction in Chapter 5. Based on the experimental results, I clarified the similarities and differences between genders and nationalities [71], which should be taken into account in model construction.

For kawaii spoon designs, all participants preferred the flower and smiley designs over the heart designs. However, males tended to prefer flower designs, and females tended to prefer smiley designs. The tendency of the kawaii selection between Japanese and Thai participants was similar. Considering each spoon design, I found that more than half of them had no differences in kawaii selection. Based on the results, I can provide suggestion to spoon manufacturers about the kawaii designs for Japanese and Thai consumers.

However, the suggestion had limitation to apply because it only showed the candidates of spoon designs but their attributes were not clarified yet. Therefore, I performed further analysis to construct model of kawaii feelings and clarify attributes of kawaii spoon designs in Chapter 5.

# Chapter 5

# Construction of Models of Kawaii Feelings for Spoon Designs

## 5.1 Background

From the evaluation of spoon designs in Chapter 4, the results had limitation to give general suggestion to design kawaii spoons. Therefore, I continued to perform data analysis to construct models of kawaii feelings for spoon designs, which can provide more general suggestion. One of the commonly-used methods to construct model is machine learning.

Machine learning has important role in many kansei engineering researches [72], [73], [74]. It is a branch of artificial intelligence that gives computers the ability to learn without being explicitly programmed [75]. Machine learning algorithms are divided into two types: supervised and unsupervised learning. Supervised learning provides algorithms to construct predictive model to learn a general rule between labelled input and desired output [76], which was employed in this research.

For this part of research, I employed support vector machine (SVM), which is one of commonly-used machine learning techniques, to classify the kawaiiness of spoon designs using their physical attributes. SVM algorithms as they have been successfully used in many researches related to image-based classification [77], [78]. SVM classifier is effective in high dimentional feature spaces, especially when the training dataset is small [79]. It can efficiently perform linear or non-linear classification using the different kernels, for example, linear, polynomial, radial basis function (RBF), and sigmoid kernels. Usually, linear and RBF kernels are commonly used as they yield good results. A research [80] showed that the linear kernel is a degenerated version of RBF kernel. Therefore, in many cases, the RBF kernel is chosen.

To provide training dataset for SVM algorithm, feature extraction is necessary. It is a method to create features or attributes that make the machine learning algorithm work. In researches related to affective engineering, many of them used shape and color as a basis to deal with the extraction of useful information from the images [77], [78], [81]. Therefore, I considered that shape and color were the key components that can be used to extract the attributes from the images of spoon designs.

There are various techniques for feature extraction. Traditional method extracts the attributes manually which often requires expensive human labor because it needs an observation by human. However, if the problem is not complicated, this method is better for reducing learning time and cost. The other method makes use of the image processing techniques to transform the images into attributes represented in numerical forms [82], [83], [84]. Since color is one of the most important information of images and has been successfully used in various applications some color spaces, such as RGB and HSV, are used to represent the extracted attributes from images [85], [86].

## 5.2 Method for Model Construction

The model construction was divided into 2 phases: training and validation phases, as shown in Figure 5.1. The training phase consists of these following steps:

1. Preparation of raw data (i.e. images of spoon designs) for feature extraction
2. Training the models using feature vector (i.e. attributes of spoon designs) and label as input to the SVM classification algorithm

The validation phase consists of the validation of the trained classifiers from training phase on their accuracy in classification. The details of each phase are described in the following sections.

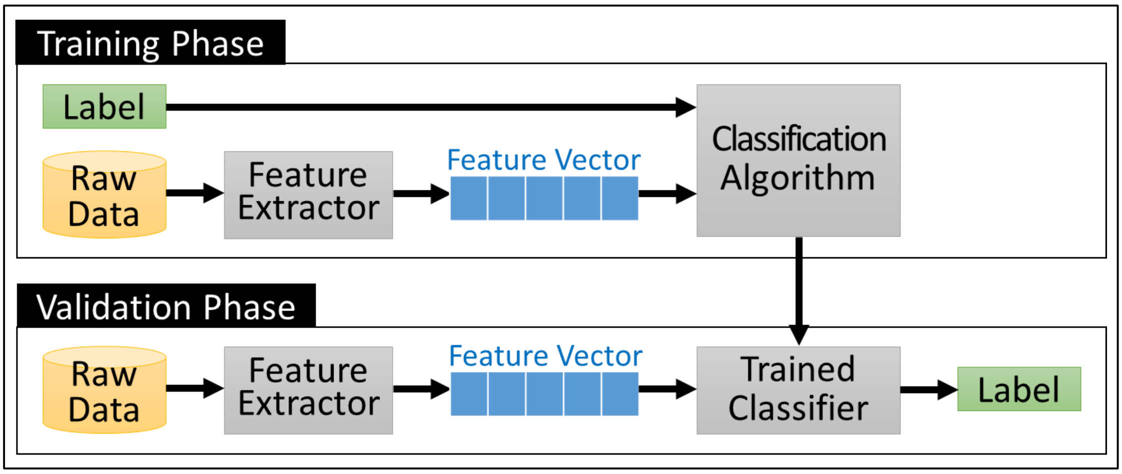



**Figure 5.1** Overall procedure of model construction

### 5.2.1 Dataset Preparation

To construct model, I employed the spoon designs, which were previously used in Chapter 4, as target products. Their attributes were not so complexed which were appropriate for the first trial of model construction. I used the average scores of 39 spoon designs from all, male, and female participants. Based on the average scores, the ranks of 39 spoon designs were calculated and divided into 3 groups (high, middle, and low rank groups) as shown in Figure 5.2. Then only spoon designs and their ranks in high rank group (top 13 ranks) and low rank group (last 13 ranks) were used as the dataset. This procedure of dataset preparation was repeatedly performed to prepare 3 datasets for all, male, and female participants.

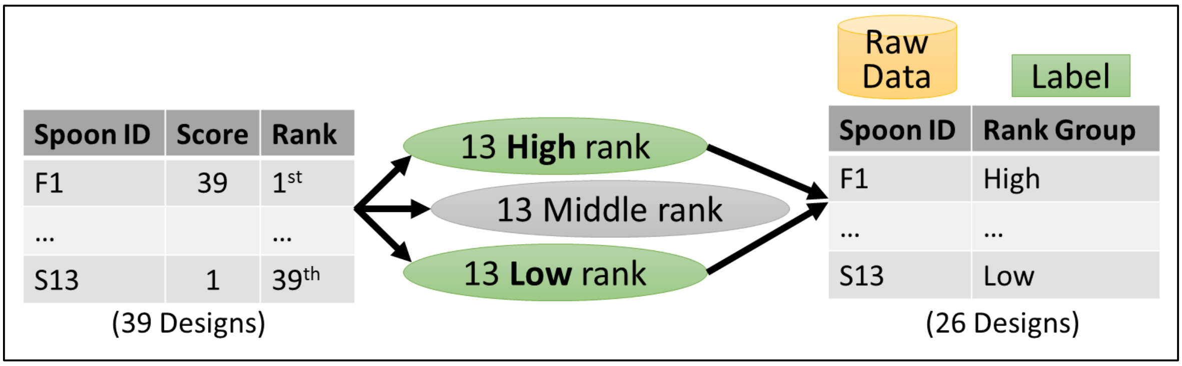



**Figure 5.2** Procedure of dataset preparation

### 5.2.2 Feature Extraction

I defined 33 physical attributes and calculated their values for the 39 spoon designs. To define the attributes, I extracted the features from the images of spoon designs into categorical or numerical forms which were necessary as input to train the model using SVM algorithm in the next step. I performed feature extraction by using two following methods.

#### 5.2.2.1 Manual Observation

This method was to manually observe the appearance of spoon designs. Based on shape and color, I defined 10 attributes as shown in Table 5.1.

**Table 5.1** List of attributes defined by manual observation method

| Attribute | Value |
|---|---|
| **Shape-based attributes** | |
| Shape | Flower / Heart / Smiley |
| Shape is repeated? | Yes / No |
| Number of shapes | (Integer) |
| Other shapes exist? | Yes / No |
| Background pattern | None / Plain color / Patterned |
| **Color-based attributes** | |
| Shape has color? | Yes / No |
| Shape has color gradient? | Yes / No |
| Background has color? | Yes / No |
| Background has color gradient? | Yes / No |
| Total number of colors | 1 / 2 / 3 / More than 3 |

### 5.2.2.2 Image Processing

Defining the attributes using only the manual observation might not be efficient enough. Thus, I also employed image processing techniques to calculate pixel values and number of pixels on the images of spoon designs. To calculate those values, I divided each image of spoon designs into three areas as follows:

- Total area (Figure 5.3 (A)): the whole image
- Shape area (Figure 5.3 (B)): the area that represents “flower”, “heart”, or “smiley” shape
- Background area (Figure 5.3 (C)): the area other than shape area

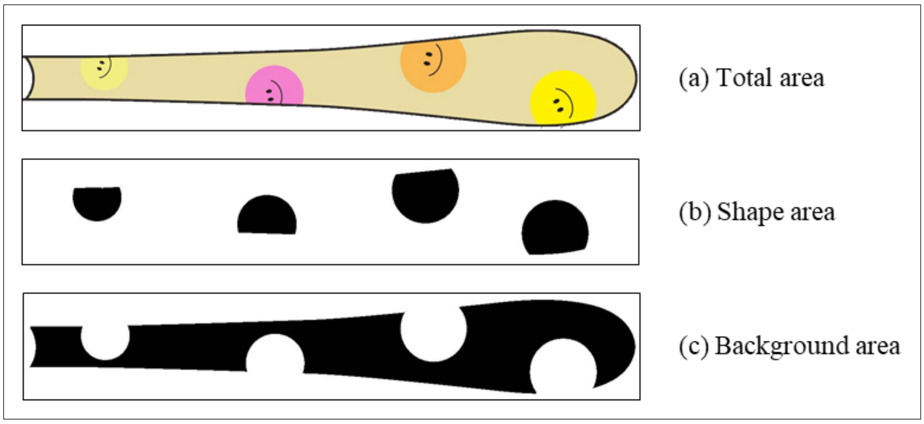



**Figure 5.3** (A) Original spoon design with “smiley” shape (B) Black pixels that represent the area of “smiley” shape (C) Black pixels that represent background area

Based on shape and color, I defined total of 23 attributes as shown in Table 5.2.

**Table 5.2** List of attributes defined by image processing method

| Attribute | Category |
|---|---|
| **Shape-based attributes** | |
| Ratio of shape area to total area | (Integer, Range = 0~100) |
| Ratio of background area to total area | (Integer, Range = 0~100) |
| Ratio of colored area to total area<br>(※White color was disregarded.) | (Integer, Range = 0~100) |
| Ratio of shape area to colored area | (Integer, Range = 0~1) |
| Ratio of background area to colored area | (Integer, Range = 0~1) |
| **Color-based attributes** | |
| Average R in total area | (Integer, Range = 0~255) |
| Average G in total area | (Integer, Range = 0~255) |
| Average B in total area | (Integer, Range = 0~255) |
| Average H in total area | (Integer, Range = 0~360) |

**Table 5.2** List of attributes defined by image processing method (Cont')

| Attribute | Category |
|---|---|
| Average S in total area | (Integer, Range = 0~100) |
| Average V in total area | (Integer, Range = 0~100) |
| Average R in shape area | (Integer, Range = 0~255) |
| Average G in shape area | (Integer, Range = 0~255) |
| Average B in shape area | (Integer, Range = 0~255) |
| Average H in shape area | (Integer, Range = 0~360) |
| Average S in shape area | (Integer, Range = 0~100) |
| Average V in shape area | (Integer, Range = 0~100) |
| Average R in background area | (Integer, Range = 0~255) |
| Average G in background area | (Integer, Range = 0~255) |
| Average B in background area | (Integer, Range = 0~255) |
| Average H in background area | (Integer, Range = 0~360) |
| Average S in background area | (Integer, Range = 0~100) |
| Average V in background area | (Integer, Range = 0~100) |

For shape-based attributes, I calculated the ratio of pixels between the areas. For example, to obtain the "ratio of pixels in shape area to total area" of a spoon design shown in Figure 5.3, I calculated the ratio of number of black pixels that represent "smiley" shape (B) to number of all pixels (A).

For color-based attributes, I employed two color spaces, which were RGB (Red, Green, Blue) and HSV (Hue, Saturation, Value/Brightness). I calculated the average pixel values in shape area, background area, and total area.

From both methods of feature extraction, I defined the total of 33 attributes of spoon designs. The extracted attributes were used in the next step.

### 5.2.3 Model Training

From the spoon designs and their rank groups described in Section 5.1.1.2 and the defined attributes described in Section 5.1.1.3, I combined them to create the dataset as shown in Figure 5.4. Each spoon design consisted of its rank group (high or low) and a set of 33 attributes with corresponding values as feature vector. The datasets for the all, male, and female participants were prepared. The 26 spoon designs and their rank groups were different among the three participant groups.

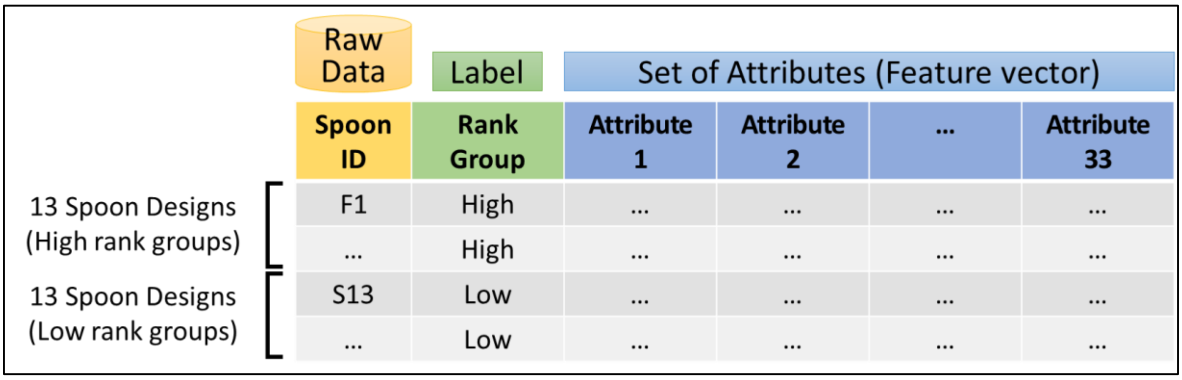



**Figure 5.4** Procedure of training a classifier using prepared dataset

I used SVM (RBF) algorithm to train the classifiers. I performed 3-fold cross validation in which 70% of the dataset was used as training set. Therefore, the classifier was trained with different data for three iterations as shown in Figure 5.5.

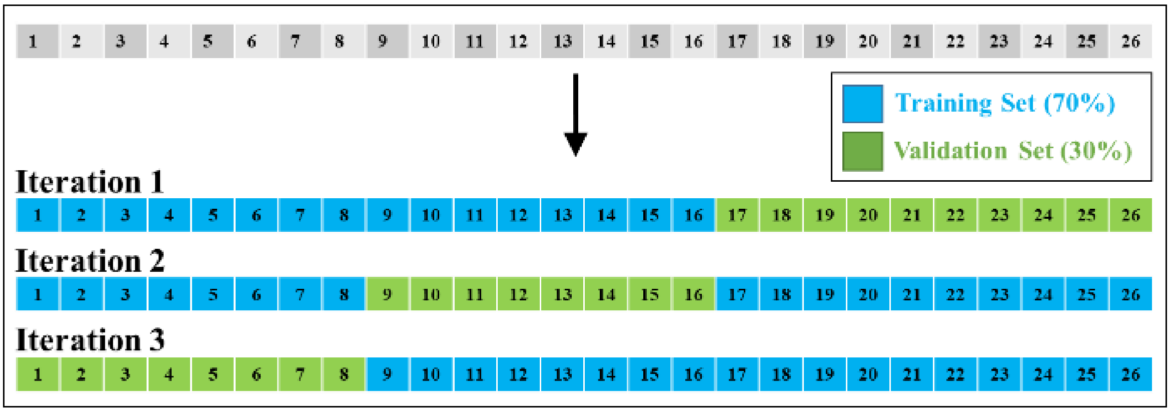



**Figure 5.5** Training and validation sets for each iteration of 3-fold cross validation

### 5.2.4 Model Validation

As previously mentioned, I performed 3-fold cross validation. For each iteration, the trained classifier was validated using the remaining 30% of the dataset. From classification results, I calculated the accuracy of each trained classifier from the number of data correctly classified. If all of the input ranks and the predicted ranks were matched, the accuracy was 100%.

## 5.3 Results of Model Construction

### 5.3.1 Classification Results

From the prediction phase, I obtained classification accuracy of the trained classifiers for the dataset of all, male, and female participants as shown in Table 5.3. Then I calculated the average accuracy of three iterations for each participant group. The average accuracy for all, male, and female participants were 65.0%, 72.5%, and 45.8%, respectively.

The average accuracy for female participants was lower than that of male participants, which reflected the result of previous research that female participants had more variety of kawaii selection than male participants.

**Table 5.3** Classification accuracy of 3-fold cross validation divided by participant groups

| **Participant Group** | **Classification Accuracy (%)** | | | |
| --- | --- | --- | --- | --- |
| | **Iteration#1** | **Iteration#2** | **Iteration#3** | **Average** |
| All participants | 62.5 | 62.5 | 70.0 | 65.0 |
| Males | 75.0 | 62.5 | 80.0 | 72.5 |
| Females | 50.0 | 37.5 | 50.0 | 45.8 |

### 5.3.2 Results of Effective Attributes

As previously mentioned that male and female participants had differences in kawaii selection, I analyzed the results of effective attributes by dividing into the results for male and female participants.

Effective attributes of the model were indicated by the relative importance (RI) which was the values obtained from SVM results. I set the threshold of RI at 0.03. For each iteration, I obtained effective attributes and their relative importance (RI). Then I selected common attributes from the three iterations in which the attributes with RI equal or more than 0.03 were included.

#### 5.3.2.1 Male participants

The effective attributes of the three iterations for male participants were shown in Table 5.4. From the selection of common attributes among three iterations, there were two effective attributes: (1) total number of colors and (2) shape.

As shown in Table 5.5, I further analyzed the values of the two effective attributes for high and low rank groups based on the ranks of the spoon designs in both groups. For high rank group, the spoon designs with many colors (more than three colors) in flower or smiley shape tended to have high ranks indicating that they were more kawaii. For low rank group, the spoon designs with less colors (less than three colors) in heart shape tended to have low ranks indicating that they were less kawaii. Examples of more and less kawaii spoon designs were shown in Figure 5.6.

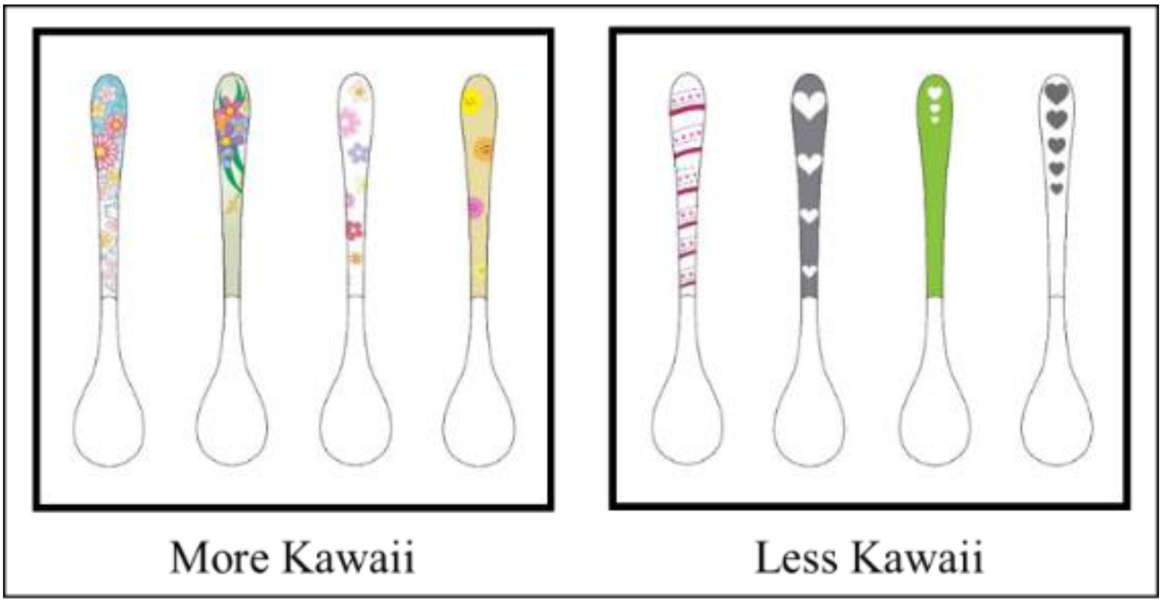



**Figure 5.6** Examples of more kawaii and less kawaii spoon designs for male participants

**Table 5.4** Effective attributes of the 3 iterations for male participants

| Iteration#1 | | Iteration#2 | | Iteration#3 | |
|---|---|---|---|---|---|
| **Attribute** | **RI** | **Attribute** | **RI** | **Attribute** | **RI** |
| Total number of colors (1) | .049 | Total number of colors (1) | .037 | Total number of colors (1) | .067 |
| Shape (2) | .040 | Other shapes exist? | .033 | Shape is repeated? | .048 |
| Shape is repeated? | .036 | Background pattern | .032 | Shape (2) | .047 |
| Ratio of shape area to total area | .034 | Average S in background area | .032 | Background pattern | .042 |
| Ratio of background area to total area | .034 | Average S in shape area | .031 | Background has color? | .038 |
| Average R in background area | .032 | Average H in shape area | .031 | | |
| Shape has color gradient? | .032 | Shape (2) | .031 | | |
| Average V in background area | .032 | Average R in total area | .031 | | |
| Average S in background area | .032 | | | | |
| Average R in shape area | .031 | | | | |

**Table 5.5** Values of effective attributes for high and low rank groups for male participants

| Attribute | Rank Group | |
|---|---|---|
| | **High Rank** | **Low Rank** |
| Total number of colors | More colors | Less colors |
| Shape | 1. Flower<br>2. Smiley | Heart |

### 5.3.2.2 Female participants

I analyzed the result of effective attributes using the same method as that of male participants previously described. The effective attributes of the three iterations for female participants were shown in Table 5.6. From the selection of common attributes, there was only one effective attribute which was shape.

I further analyzed the values of the effective attributes for high and low rank groups as shown in Table 5.7. For high rank group, the spoon designs with flower or smiley shape tended to have high rank indicating that they were more kawaii. For low rank group, the spoon designs with heart shape tended to have low rank indicating that they were less kawaii.

**Table 5.6** Effective attributes of the 3 iterations for female participants

| Iteration#1 | | Iteration#2 | | Iteration#3 | |
|---|---|---|---|---|---|
| **Attribute** | **RI** | **Attribute** | **RI** | **Attribute** | **RI** |
| Shape | .047 | Shape is repeated? | .059 | Shape | .042 |
| Average R in shape area | .035 | Shape | .057 | Background pattern | .032 |
| Average V in shape area | .034 | Average S in background area | .036 | Background has color? | .032 |
| Ratio of shape area to total area | .033 | Average B in total area | .032 | Ratio of shape area to total area | .032 |
| Ratio of background area to total area | .033 | Average G in total area | .032 | Ratio of background area to total area | .032 |
| Background pattern | .033 | Average H in total area | .031 | Shape is repeated? | .031 |
| Background has color? | .033 | Average H in background area | .031 | Average S in shape area | .031 |
| Average S in shape area | .031 | Average S in total area | .031 | | |
| Average H in Background | .031 | | | | |
| Total number of colors | .031 | | | | |

**Table 5.7** Values of effective attributes for high and low rank groups for female participants

| Attribute | Rank Group | |
|---|---|---|
| | **High Rank** | **Low Rank** |
| Shape | 1. Smiley<br>2. Flower | Heart |

## 5.4 Discussion and Conclusion

In this part of research, I constructed models of kawaii feelings for spoon designs [87]. I used the ranks of 39 spoon designs from previous experiment (described in Chapter 4) and defined 33 attributes based on shape and color. They were used to construct the models of kawaii feelings. The models were constructed using SVM algorithm to perform classification for the kawaiiness of spoon designs.

From the classification results, the accuracy of model for female participants was lower than that of male participants. From the results of effective attributes, shape was the only effective attribute for female participants. These two results reflected the result of previous experiment (Chapter 4) that female participants had more variety of kawaii selection than male participants. Therefore, I suggest that the manufacturer should take genders into account to design kawaii spoons.

From the comparison of attributes between male and female participants, shape was the common effective attribute for both participant groups. However, there were some differences that flower designs tended to be more kawaii for males, while smiley designs tended to be more kawaii for females.

In this chapter, I clarified effective attributes for kawaii spoon designs for male participants (total number of colors and shape) and female participants (shape). For spoon manufacturers, these attributes should be taken into account in order to design kawaii spoons. Actually, there are many more variations than 39 spoon designs. However, I used only 39 spoon designs to simplify the feature extraction for model construction using SVM algorithm. If more variations of spoon designs are employed, there is possibility that other effective attributes for kawaii spoon designs can be clarified.

Even SVM algorithm has a limitation that it requires feature extraction, my model can be applied to the products if we define their attributes.

# Chapter 6

# Relationship between Physical Attributes of Spoon Designs and Eye Movements Caused by Kawaii Feelings

## 6.1 Background

In Chapter 5, I constructed models of kawaii feelings for spoon designs. As the results, I obtained candidates of effective attributes for kawaii spoon designs. In this chapter, I employed eye tracking to clarify effective attributes to design kawaii spoons [88]. The objectives are as follows:

1. To clarify the relationship between attributes of spoon designs and eye movement indexes caused by kawaii feelings
2. To confirm the usefulness of eye movement indexes clarified in previous experiment (Chapter 3).

## 6.2 Experiment Method

### 6.2.1 Selection of Attributes for Spoon Designs

First, I employed the evaluation results of 39 spoon designs from our previous experiment. Only the results of Japanese participants were used in this experiment. I divided 39 spoon designs into 3 groups based on their ranks: high-rank group, middle-rank group, and low-rank group. The spoon designs in high-rank group were selected from the top 13 designs with highest ranks. Similarly, the spoon designs in middle-rank and low-rank groups were the next 13 designs and the last 13 designs with lowest ranks, respectively.

Since I performed the experiment using eye tracking, the spoon designs should have a large difference in kawaiiness. Therefore, I used only 26 spoon designs from high-rank and low-rank groups.

From the evaluation results of spoon designs in Chapter 4, I performed feature extraction to create the attributes of the spoon designs. This process transformed the input from raw data (i.e. images of spoon designs) into statistical data. I obtained the total of 33 attributes of spoon designs.

Next, I used the decision tree algorithm (C5.0) to select effective attributes. The inputs were 26 spoon designs in which each spoon contained 33 attributes. The target was the rank group, either high or low. From the decision tree result, I obtained four effective attributes as shown in Figure 6.1 Decision tree result. “Shape” was the most effective attribute. For “flower shape,” “with/without background color” and “number of shapes” were the other effective attributes. For “smiley shape,” “the ratio of shape area to colored area” was the other effective attribute.

I made the assumptions from the decision tree result as follows:

1) "Flower shape" and "smiley shape" are more kawaii than "heart shape."
2) For the spoon designs in "flower shape," those with "background color" are more kawaii than those without it.
3) For the spoon designs in "flower shape" and "without background color," those with "number of flowers" more than 4 are more kawaii than those of less than or equal to 4.

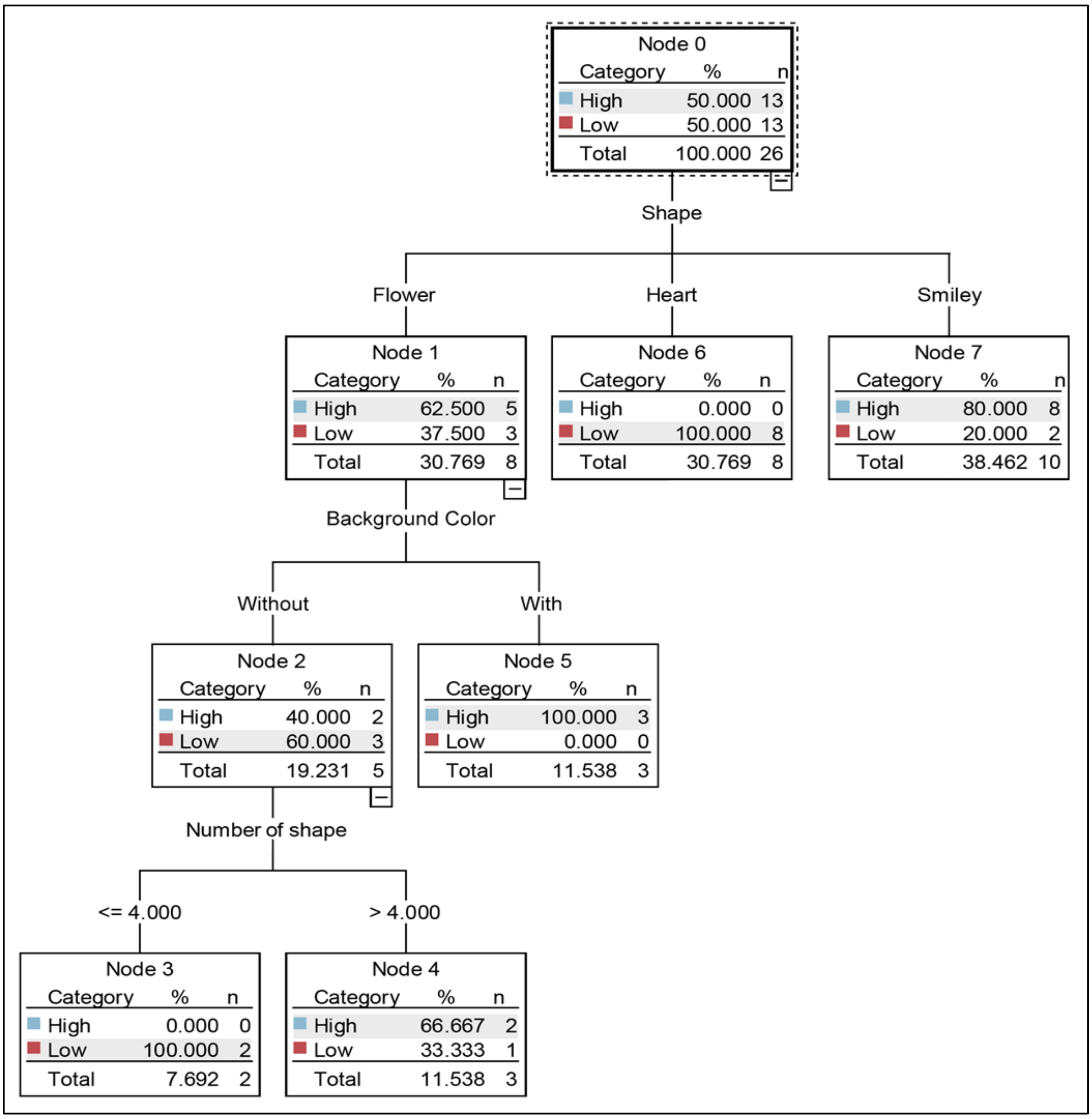



**Figure 6.1** Decision tree result

### 6.2.2 Candidates of Spoon Designs

In this experiment, only flower designs were employed based on their preferences in the result of previous experiment described in Chapter 4. Then, I used two effective attributes for "flower shape" ("with/without background color" and "number of shapes") to select the candidates of spoon designs.

To balance between the attributes and average ranks, I selected four candidates of spoon designs (Figure 6.2). As shown in Table 6.1, spoon designs were divided equally by background color and number of shapes. Moreover, average ranks, which were the results from 10 female participants in previous experiment described in Chapter 5, were distributed from 1$^{st}$ to 39$^{th}$ ranks.

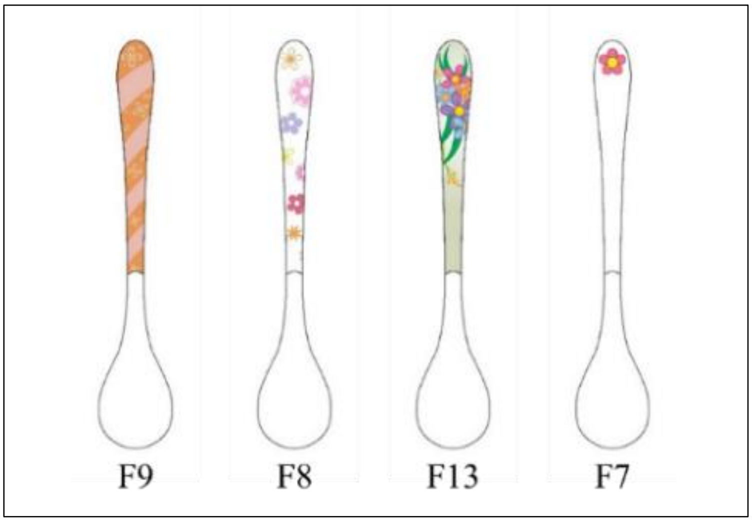



**Figure 6.2** Spoon designs for evaluation

**Table 6.1** Candidates of spoon designs and their corresponding physical attributes and average ranks

| Design ID | With/without background color | Number of shapes | Average Rank |
|---|---|---|---|
| F9 | With | > 4 | 8 |
| F8 | Without | > 4 | 19 |
| F13 | With | ≤ 4 | 34 |
| F7 | Without | ≤ 4 | 38 |

### 6.2.3 Comparison System

I modified a spoon comparison system based on the problems of previous experiment that evaluated kawaii illustrations described in Chapter 3. The system used four spoon designs as visual stimuli (Figure 6.2). The four spoon designs were displayed in pairs with left-right counterbalanced. The total number of compared pairs was 12. All of the system content was described in Japanese. The structure of the system is described as follows:

1. Top page: questionnaire explanation
2. Consent form: brief explanation about experiment and permission to use their data
3. Selection of participant's gender
4. Explanation of spoon design selections: the spoon designs were displayed in pairs for five seconds. Selection of more kawaii spoon designs was performed using the keyboard's left or right arrow keys.
5. Spoon designs comparison:
    a. A cross sign (+) appeared at the middle of the display for 2.5 seconds to fix the eyes at the same position before each comparison. (Figure 6.3)
    b. The pairs of spoon designs were randomly displayed with a 5-second countdown timer. Selections of more kawaii spoon designs were performed using the keyboard's left or right arrow keys. (Figure 6.4)
6. Questionnaire: three subjective questions were asked: reason for selecting the spoon designs (free description), most kawaii spoon design, and favorite spoon design.
7. Last page: the system explained that the comparison was finished.

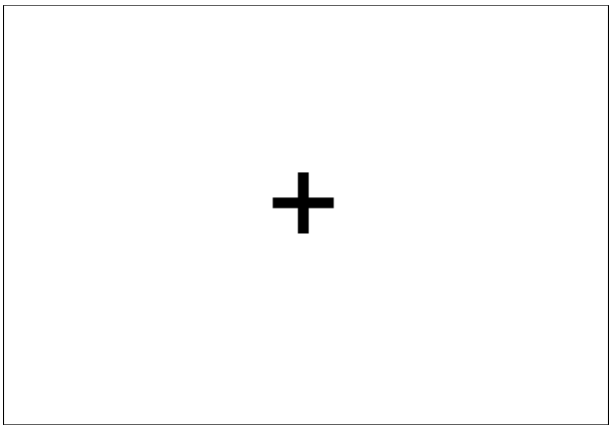


**Figure 6.3** Screenshot of spoon comparison system displaying cross sign

**Figure 6.4** Screenshot of spoon comparison system displaying two spoon designs and countdown timer

### 6.2.4 Experimental Setup and Procedure

Figure 6.5 shows the experimental setup. The comparison system was accessed from the eye tracking system through a web browser, i.e., Google Chrome, whose system ran on a separate PC due to limited resources. The eye tracking system employed the EyeTech TM3 non-intrusive eye tracker (EyeTech Digital Systems, Inc.) and QG-PLUS software (DITECT Co., Ltd.) to record the eye movements and display the eye tracking data. I used a 19-inch LCD monitor with resolution of 1280 x 1024 pixels.

The following are the experimental procedures:

1. Participant sat on chairs in front of the PC.
2. Participant read the explanation of the experiment.
3. I calibrated the eyes of the participant.
4. I showed the spoon comparison system and started recording eye movements.
5. Participant selected kawaii spoon designs from 12 pairs.
6. Participant answered the questionnaire.
7. I stopped recording the eye movements.

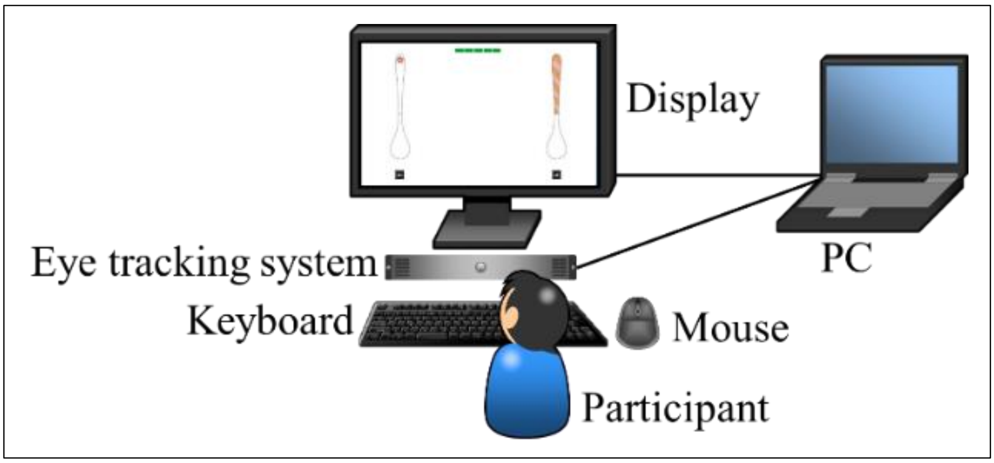



**Figure 6.5** Experiment setup of spoon design comparison

## 6.3 Experimental Results and Discussion

### 6.3.1 Participant

I performed the experiment with a female participant who was 19 years old.

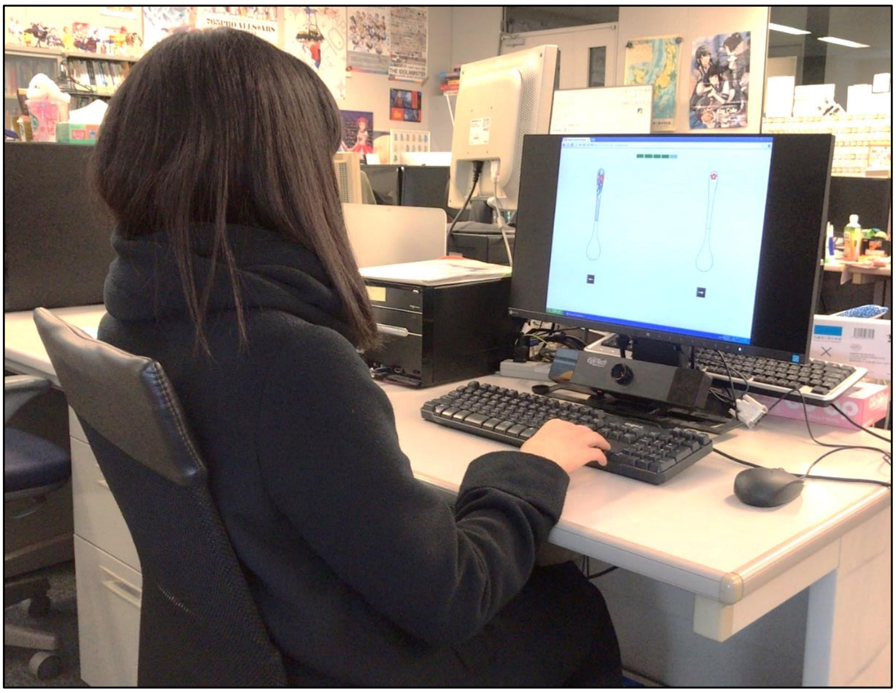


**Figure 6.6** Experiment scene of comparison of spoon designs during a record of eye tracking

### 6.3.2 Cumulative Result

I collected the cumulative results (the kawaii scores) from the comparison of spoon designs. All combinations of two spoon designs with left-right counterbalanced were compared for 12 times. Each spoon design appeared for six times in total. The kawaii scores were calculated from the total number of selection for each spoon design from 12 times of comparison. The spoon designs and their kawaii scores were shown in Table 6.2. The order of spoon designs from highest to lowest kawaii scores was as follows: F9 > F13 > F7 > F8. From this order, only F9 resembled the average rank (Table 6.1). The orders of the other three spoon designs were different from the average ranks.

**Table 6.2** Spoon designs and their kawaii scores

| Design ID | Kawaii Score |
|---|---|
| F9 | 6 |
| F8 | 0 |
| F13 | 4 |
| F7 | 2 |

### 6.3.3 Questionnaire Result

The questionnaire result consists of three parts as follows:

- Softness of color was the reason for selecting the spoon designs.
- She selected F9 as the most kawaii spoon design.
- She selected F13 as favorite spoon design.

The cumulative result, questionnaire result, and average ranks in (Table 6.1) resembled that F9 was the most kawaii.

### 6.3.4 Results of Eye Tracking Data

To analyze eye movement data, I employed fixation and Area of Interest (AOI) as in previous research described in Chapter 3. For this experiment’s analysis, I defined two AOIs for the left-side and right-side illustrations on the spoon’s handles (Figure 6.7). The shape and the size of the AOIs were identical to balance the analysis areas.

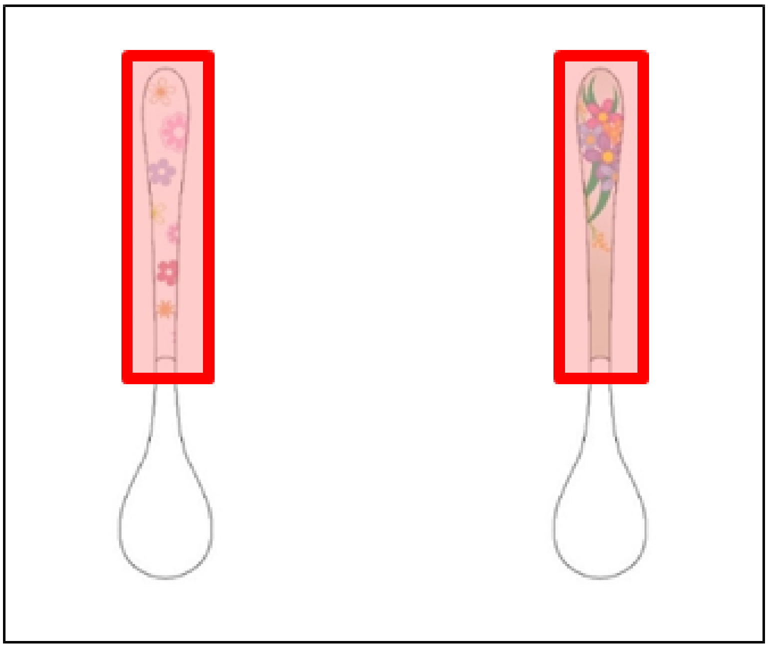


**Figure 6.7** Two AOIs with identical shape and size (red brackets) showing areas included in the analysis of eye movement data in a pair of spoon designs

I analyzed the eye movement data by employing the eye movement indexes obtained from previous study that evaluated the kawaii illustrations (Chapter 3) in order to confirm that they are useful to evaluate kawaii feelings not only for kawaii illustrations but also kawaii spoon designs. In addition, in previous study, I employed only the eye movement data of the first half of comparison. The first-half eye movement data was meaningful because the participants actually considered the illustrations based on kawaii feelings. For the latter-half comparison, the participants only identified the illustrations and selected the ones that they already made decision as the most kawaii. Therefore, I also employed the first half of comparison (six pairs) in the analysis of this experiment. The results were described as follows:

- **Total AOI duration**

This index was sum of durations of all eye positions inside AOI. I analyzed the total AOI durations of each spoon design. Figure 6.8 shows the total AOI duration and the order of pair of comparison for 12 pairs. For the first six pairs, the total AOI duration of F9 tended to be higher than the other spoon designs, especially the 1st and 3rd pairs. Similarly, F9 had highest sum of total AOI duration among all four spoon designs (Table 6.3).

On the other hand, F7 had lowest total AOI duration. The reason was possibly that this spoon design was much simpler than the other three spoon designs. Consequently, the participant did not need to take long time to consider. From this result, I suggested that the complexity of objects should be similar in order to compare their kawaiiness.

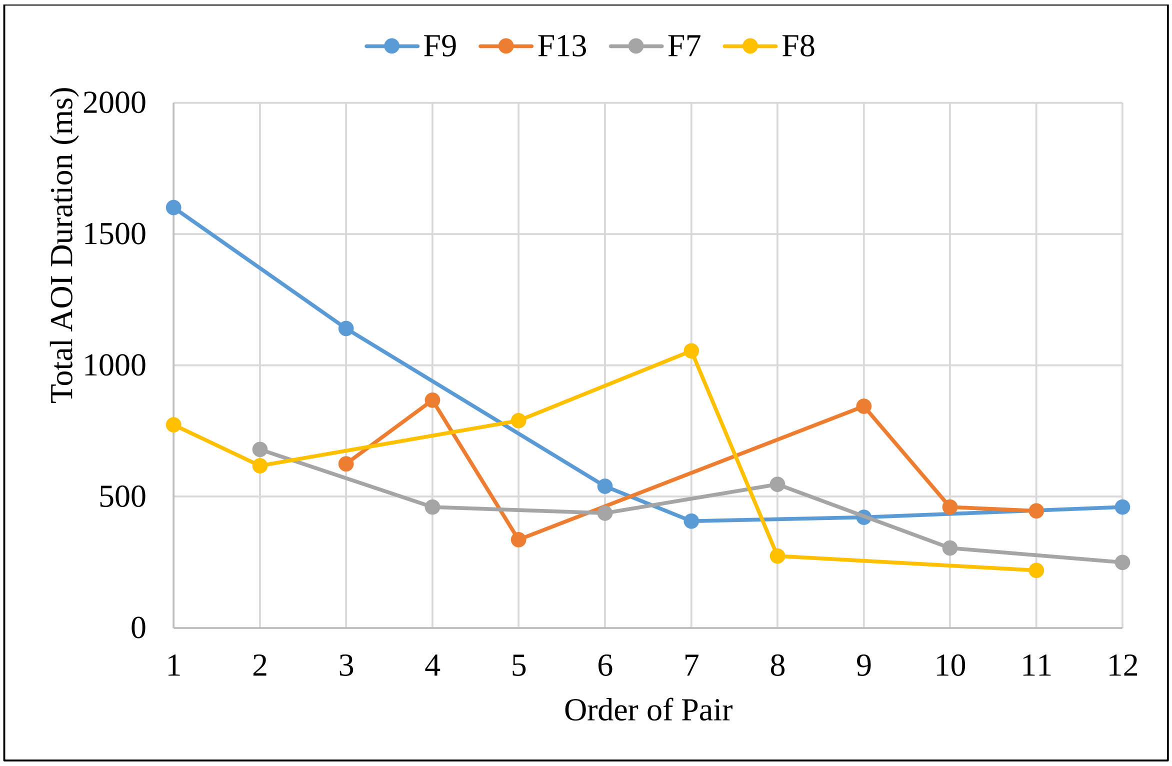



**Figure 6.8** Total AOI durations of four spoon designs for 12 pairs of comparison

**Table 6.3** Sum of total AOI duration of four spoon designs for the first half of comparison

| Design ID | Sum of Total AOI Duration (ms) |
|---|---|
| F9 | 3281.25 |
| F8 | 2179.69 |
| F13 | 1828.13 |
| F7 | 1578.13 |

- **Total number of fixations**

This index was sum of all fixations inside AOI. Figure 6.9 shows the total number of fixations and the order of pair of comparison for 12 pairs. For the first six pairs, the total number of fixations of F9 tended to be higher than the other spoon designs. Similarly, F9 had highest total number of fixations among all four spoon designs (Table 6.4).

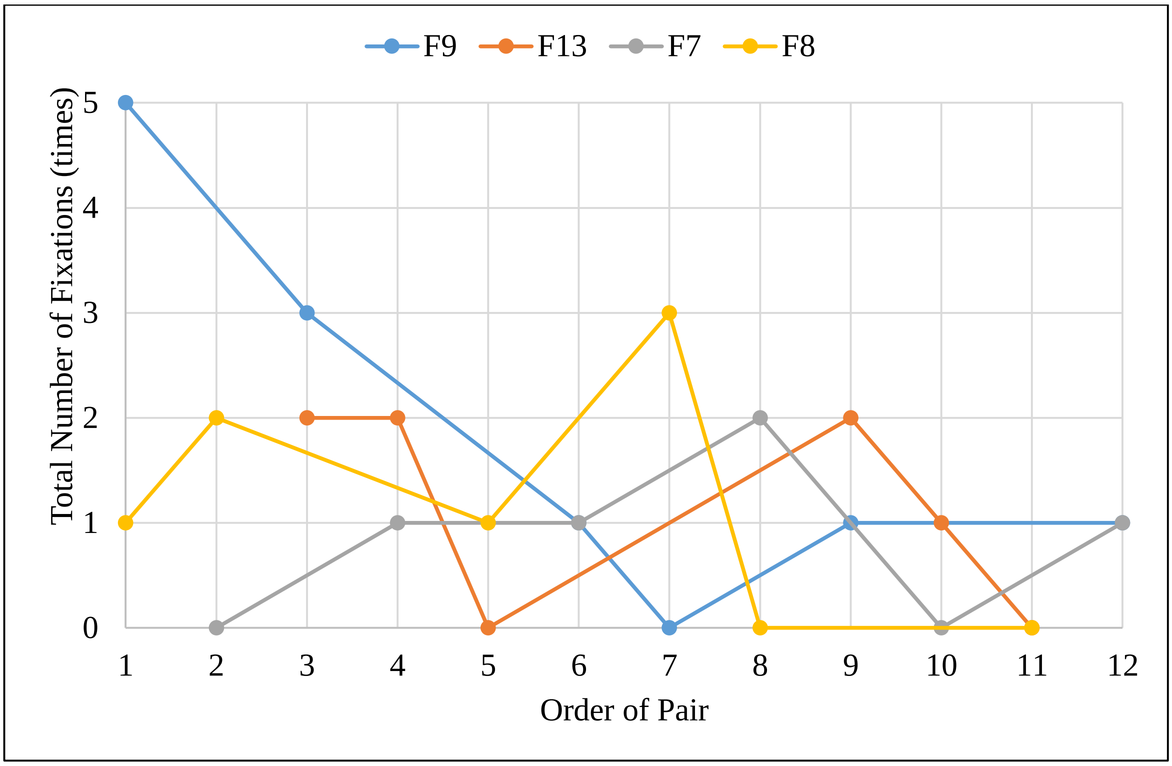



**Figure 6.9** Total number of fixations (times) of four spoon designs for 12 pairs of comparison

**Table 6.4** Sum of total number of fixations of four spoon designs for the first half of comparison

| Design ID | Total Number of Fixations (times) |
|---|---|
| F9 | 9 |
| F8 | 4 |
| F13 | 4 |
| F7 | 2 |

For both total AOI duration and total number of fixations, the participant considered the kawaiiness of spoon designs only during the first half of comparison. Therefore, only the first-half eye movement data was meaningful for the analysis which resembled the result of our previous study on kawaii illustrations (Chapter 3).

In addition, the results between total AOI duration and total number of fixations were similar. The consistency between these two results indicated that these two eye movement indexes had similar tendency.

### 6.3.5 Comparison Results among Physical Attributes, Cumulative Result, and Eye Movement Data

As shown in Table 6.5, the first column shows two groups of physical attributes divided by “with/without background color” attribute (2nd assumption described in the last part of Section 6.2.1) and “number of shapes” attribute (3rd assumption described in the last part of Section 6.2.1). Note that the 3rd assumption applies to those “without background color” only.

In addition, I ordered the spoon designs from highest to lowest scores, and the two eye movement indexes from highest to lowest values. The results were shown in Table 6.5. The numbers inside brackets show the values used for ordering or grouping.

**Table 6.5** Spoon designs ordered/grouped by kawaii scores, attribute and eye movement indexes

| **Physical attribute** | | **Kawaii Score** | **Eye movement index** | |
|---|---|---|---|---|
| **With/without background color** | **Number of shapes** | | **Total AOI Duration** | **Total number of fixations** |
| F9, F13 (With) | | F9 (6) | F9 (3281.25) | F9 (9) |
| | | F13 (4) | F8 (2179.69) | F8, F13 (4) |
| F7, F8 (Without) | F8 (> 4) | F7 (2) | F13 (1828.13) | |
| | F7 (≤ 4) | F8 (0) | F7 (1578.13) | F7 (2) |

*Remark.* For “number of shapes” attribute, only the spoon designs without “background color” are applicable.

I analyzed the relationships between physical attributes of spoon designs (i.e. “with/without background color” and “number of shapes”), cumulative result (i.e. kawaii scores), and eye movement indexes (i.e. total AOI duration and total number of fixations). The results are described as follows:

**1) Relationships between physical attributes and kawaii scores**

From the 2nd and 3rd assumptions described in the last part of Section 6.2.1, I expected two following results:

1. F9 and F13 (spoon designs with background color) had higher kawaii scores than F7 and F8 (spoon designs without background color). (2nd assumption)
2. F8 (number of shapes more than 4) had higher kawaii scores than F7 (number of shapes less than or equal to 4). (3rd assumption)

As shown in Table 6.5, the kawaii scores of F9 and F13 were higher than those of F7 and F8 which supported our first expected result. Therefore, if I increase the number of participants, the assumption that "spoon designs with background color have higher kawaii scores" can be confirmed. However, the kawaii score of F7 was higher than that of F8 which conflicted with our second expected result. Further study is necessary to clarify the relationship between "number of shapes" attribute and kawaii scores.

**2) Relationships between kawaii scores and eye movement indexes**

In previous study described in Chapter 3, I concluded that the total AOI duration and the total number of fixations will be high if the kawaii scores are high. I analyzed the relationships to confirm whether the results of this experiment supported our previous study or not.

As shown in Table 6.5, F9 had highest kawaii score and had highest values of both eye movement indexes (total AOI duration and total number of fixations), which supported our previous study. However, the tendency of the other three spoon designs was still unclear. If I increased the number of participants, I can confirm whether the results support our previous study or not, and whether total AOI duration and total number of fixations are useful indexes to evaluate kawaii feelings for spoon designs or not.

**3) Relationships among physical attributes, kawaii scores, and eye movement indexes**

From the 2$^{nd}$ and 3$^{rd}$ assumptions described in the last part of Section 6.2.1, I expected the same orders for physical attributes, kawaii scores, and eye movement indexes. The expectations were as follows:

1. Spoon designs with "background color" had higher kawaii scores and higher values of eye movement indexes than those without it. (2$^{nd}$ assumption)
2. For spoon designs without "background color", those with "number of shapes" more than 4 had higher kawaii scores and higher values of eye movement indexes than those of less than or equal to 4. (3$^{rd}$ assumption)

From the order comparisons for physical attributes, kawaii scores, and eye movement indexes, the results were as follows:

- The order of total number of fixations was partially consistent with those of kawaii scores, “with/without background color” attribute, and “number of shapes” attribute. This result supported both expectations.
- The order of total AOI duration was consistent with that of “number of shapes” attribute, but different from those of kawaii scores and “with/without background color” attribute. This result partially supported the second expectation.

In addition, I obtained similar tendency from the order comparisons among “with/without background color” attribute, kawaii scores, and two eye movement indexes as follows:

- F9 was in highest order.
- F13 was in the middle order.
- F7 or F8 were in the lowest order.

## 6.4 Conclusion

I experimentally evaluated kawaiiness of spoon designs using eye tracking. I performed decision tree to select useful attributes to design kawaii spoons. I selected the four flower spoon designs based on selected attributes. Then I experimentally evaluated these spoon designs using a spoon comparison system with eye tracking device. I obtained the experimental results as summarized below.

- From cumulative result, the four spoon designs had different kawaii scores. F9 had highest kawaii scores which resembled the average rank and the questionnaire result. However, the orders of other three spoon designs based on kawaii scores were different from the average ranks.

- From the analysis of eye movement indexes, the results between total AOI duration and total number of fixations had similar tendency for all spoon designs.

- For the relationship between physical attributes and kawaii scores, I made assumption that spoon designs with background color were more kawaii than those without it. The kawaii scores of F9 and F13, which were spoon designs with background color, were higher than F7 and F8, which were those without background color. This result supported the assumption.

- For the relationship between kawaii scores and eye movement indexes, our previous study (Chapter 3) concluded that the total AOI duration and total number of fixations will be high if the kawaii scores are high. For this experiment, the result of F9 supported our previous study. However, the results of the other three spoon designs were still unclear.

- For the relationship between physical attributes and eye movement indexes, we compared the orders of spoon designs for physical attributes, kawaii scores, and each of the eye movement indexes. The order comparison for total number of fixations showed better result than that of total AOI duration. Besides, at least F9 showed consistent orders among “with/without background color” attribute and two eye movement indexes.

Since number and variations of spoon designs and number of participant were limited, I can confirm only following two candidates of useful eye movement indexes to clarify effective attributes to design kawaii spoons:

- Total AOI duration
- Total number of fixations

# Chapter 7

# Construction of Models of Kawaii Feelings for Cosmetic Bottles and Their Relationship with Eye Movements

## 7.1 Background

In this chapter, I targeted at cosmetic bottles. Various researches have studied the factors that influenced buying behavior of cosmetic products. Researches suggested that the attractive packaging of perfumes [89] and cosmetic products [90] was one of the highly-prioritized factors that influenced the purchase decision. Also, research [91] concluded that packaging of cosmetic products had fairly strong influence in purchasing for Bangkok male consumers.

Since the researches revealed that packaging of cosmetic product strongly influenced the buying decision, I confirmed that this product was worthy to be employed in my study.

In Chapter 5, I constructed models of kawaii feelings for spoon designs using the Support Vector Machine (SVM) algorithm. In this chapter, I continued to construct models of kawaii feelings for cosmetic bottles. However, SVM algorithm has limitation that the feature extraction was necessary to prepare the dataset as input for model construction [72], which could not be employed for cosmetic bottles because they have complexed attributes. To solve the limitation, a new method for model construction for cosmetic bottles was necessary. I employed a Deep Convolutional Neural Network (CNN) algorithm in which the feature extraction is not required because it can use images as input.

Deep CNN is one of the deep learning algorithm which is a kind of Artifical Neural Networks (ANN) with deep architecture. In ANN algorithms, even after the development of algorithm, its performance was still insufficient due to the architecture with limited number of layers [92]. Deep learning is capable of achieving state-of-the-art performance on a dataset with complexed non-linear relationships [93]. The architecture of deep CNN algorithm consists of one or more convolutional layers for feature learning and followed by one or more fully connected layers as in a typical multilayer ANN for classification [94] (Figure 7.1). Deep CNN algorithm has been successfully applied to various domains especially detection, segmentation, and recognition of images [95], [96]. One of its main advantages that makes its usage become increasing popular is that it does not require manual feature extraction as in conventional machine learning algorithm like SVM, but the features are learned directly inside its algorithm [97].

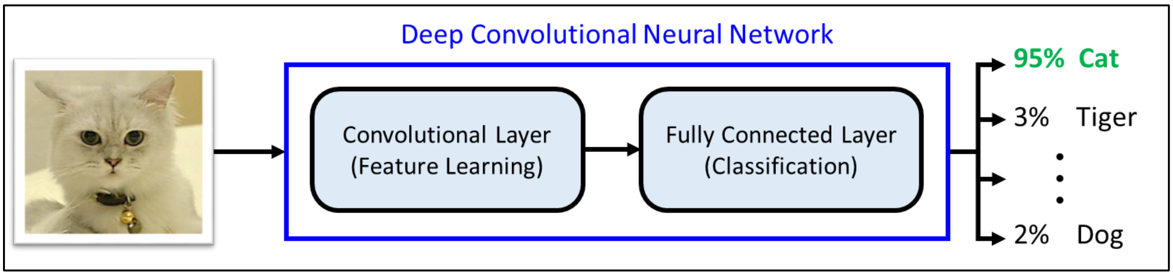



**Figure 7.1** Deep Convolutional Neural Network Architecture

## 7.2 Data Collection on Evaluation of Kawaiiness for Cosmetic Bottles

### 7.2.1 Experiment Method

I collected cosmetic bottle images and evaluated their kawaiiness to use those data to construct the models in the next step. The details are described in the following sections.

#### 7.2.1.1 Data Collection

I collected 1,048 online images of cosmetic bottles, all of which are actual products that are currently on sale (Figure 7.2).


**Figure 7.2** Example of cosmetic bottle images (photos by www.pngimg.com, licensed under Creative Commons CC BY-NC 4.0)

#### 7.2.1.2 Experimental Setup and Procedure

I experimentally evaluated the kawaiiness of the cosmetic bottle images. Since the number of images was large, I built a questionnaire system to facilitate the evaluation. The system showed each image on a screen one at a time. I used a 13.3-inch laptop with a resolution of 3200x1800 pixels.

The following are the experimental procedures:

1. Top page: explanation of experiment
2. Consent form: brief explanation about experiment and permission to use their data
3. Recording of gender and age
4. Explanation of evaluations: each cosmetic bottle image is displayed, and participants evaluated if whether is kawaii or not kawaii using the keyboard's left or right arrow keys respectively.
5. Evaluation of cosmetic bottle images: 1,048 images are displayed and evaluated by each participant. A sample screenshot is shown in Figure 7.3.
6. After the participants submitted their questionnaires, the evaluation results were saved in a database.


**Figure 7.3** Example of a page in questionnaire system showing a cosmetic bottle image and arrows used for evaluation

### 7.2.2 Experimental Results and Discussion

I performed the experiment with the following participants.

- 15 Thai volunteers: ten females (average age = 28.1, SD = 2.2) and five males (average age = 28.6, SD = 1.9)

- 20 Japanese volunteers: ten females (average age = 21.8, SD = 0.7) and ten males (average age = 21.7, SD = 0.7)

I categorized the number of cosmetic bottle images evaluated by each participant as kawaii or not kawaii. Based on the evaluations, all of the images were divided into kawaii or not-kawaii groups. The result of Thai participants are shown in Table 7.1, and that of Japanese participants are shown in Table 7.2.

To provide balanced data between the kawaii and not-kawaii groups for the model construction in the next step, I calculated the ratio of the number of images between the kawaii (A) and not-kawaii (B) groups. Then we defined whether the ratio of each participant was considered balanced or not. If the ratio was equal or close to 1:1, the data was considered balanced. As the results, eight Thai and 14 Japanese participants were selected for further analysis.

**Table 7.1** Evaluation Results of Cosmetic Bottle Images of Thai Participants

| Participant ID (Gender) | Number of Images | | Ratio (A : B) | Balanced Data |
|---|---|---|---|---|
| | Kawaii (A) | Not kawaii (B) | | |
| P01 (F) | 449 | 599 | 1 : 1.3 | Yes |
| P02 (F) | 627 | 421 | 1.5 : 1 | Yes |
| P03 (F) | 322 | 726 | 1 : 2.3 | Yes |
| P04 (F) | 136 | 912 | 1 : 6.7 | No |
| P05 (F) | 386 | 662 | 1 : 1.7 | Yes |
| P06 (F) | 72 | 976 | 1 : 13.6 | No |
| P07 (F) | 116 | 932 | 1 : 8 | No |
| P08 (F) | 73 | 975 | 1 : 13.4 | No |
| P09 (F) | 123 | 925 | 1 : 7.5 | No |
| P10 (F) | 698 | 350 | 2 : 1 | Yes |
| P11 (M) | 79 | 969 | 1 : 12.3 | No |
| P12 (M) | 623 | 425 | 1.5 : 1 | Yes |
| P13 (M) | 191 | 857 | 1 : 4.5 | No |
| P14 (M) | 273 | 775 | 1 : 2.8 | Yes |
| P15 (M) | 672 | 376 | 1 : 1.8 | Yes |

**Table 7.2** Evaluation Results of Cosmetic Bottle Images of Japanese Participants

| Participant ID (Gender) | Number of Images | | Ratio (A : B) | Balanced Data |
|---|---|---|---|---|
| | Kawaii (A) | Not kawaii (B) | | |
| P01 (F) | 241 | 807 | 1 : 3.3 | Yes |
| P02 (F) | 180 | 868 | 1 : 4.8 | No |
| P03 (F) | 611 | 437 | 1.4 : 1 | Yes |
| P04 (F) | 446 | 602 | 1 : 1.3 | Yes |
| P05 (F) | 149 | 899 | 1 : 6 | No |
| P06 (F) | 424 | 624 | 1 : 1.5 | Yes |
| P07 (F) | 676 | 372 | 1.8 : 1 | Yes |
| P08 (F) | 175 | 873 | 1 : 5 | No |
| P09 (F) | 248 | 800 | 1 : 3.2 | Yes |
| P10 (F) | 519 | 529 | 1 : 1 | Yes |
| P11 (M) | 731 | 317 | 2.3 : 1 | Yes |
| P12 (M) | 143 | 905 | 1 : 6.3 | No |
| P13 (M) | 468 | 580 | 1 : 1.2 | Yes |
| P14 (M) | 435 | 613 | 1 : 1.4 | Yes |
| P15 (M) | 532 | 516 | 1 : 1 | Yes |
| P16 (M) | 459 | 589 | 1 : 1.3 | Yes |
| P17 (M) | 290 | 758 | 1 : 2.6 | Yes |
| P18 (M) | 218 | 830 | 1 : 3.8 | No |
| P19 (M) | 124 | 924 | 1 : 7.5 | No |
| P20 (M) | 500 | 548 | 1 : 1.1 | Yes |

Next, I considered the consistency of evaluation results among participants for each nationality by using two-step cluster analysis. If the evaluation results among participants were similar, they will be clustered into the same group.

For Thai participants, the number of clusters was two groups in which four participants were equally clustered into each group. However, using the results of four participants for model construction was considerably too few. Therefore, I used the evaluation results of all eight participants for model construction in the next step.

For Japanese participants, the number of clusters was two groups in which 11 participants were clustered into the first group and the other 3 participants were clustered into the second group. Therefore, I used only the majority of evaluation results (11 participants) for model construction in the next step.

## 7.3 Model Construction of Kawaii Feelings for Cosmetic Bottles

### 7.3.1 Method for Model Construction

#### 7.3.1.1 Dataset Preparation

For Thai participants, I used the evaluation results of eight participants from the previous step as the dataset. It consisted of 8,384 images that were classified into kawaii (4,050 images) and not-kawaii (4,334 images) groups.

Since the results were from eight participants, there were eight same images in the dataset. However, they might be classified into both kawaii and not-kawaii group according to the evaluation of each participant, which might cause inconsistency. However, we considered that the inconsistency was also important to indicate how much each image contributed to kawaii or not-kawaii group. Therefore, we used all images for model construction.

To prevent model overfitting problems [98], I used k-fold cross-validation (k=8). As the dataset contained the results of eight participants, we selected eight folds so that the dataset could be divided into eight subsets without repetition of the same images in the same subset. The method to divide the dataset is described in these following steps (Figure 7.4):

1. For each participant, the images were equally divided into eight subsets for both the kawaii and not-kawaii groups.
2. To avoid the repetition of the same images in the same subsets, some images in a subset were swapped with others of the same participant. (To be done until all images in each part were different)
3. For all participants, seven subsets (v1 to v7) were used as training data. The remaining one (v8) was used as testing data.
4. The training data from the kawaii and not-kawaii groups were combined into a *training set*, which contained 87.5% of all the images.
5. The testing data from the kawaii and not-kawaii groups were combined into a *testing set*, which contained the remaining 12.5% of the images.

Note that each subset was rotated and used once as testing data in Step 2). Thus I prepared a total of eight different training and testing sets.

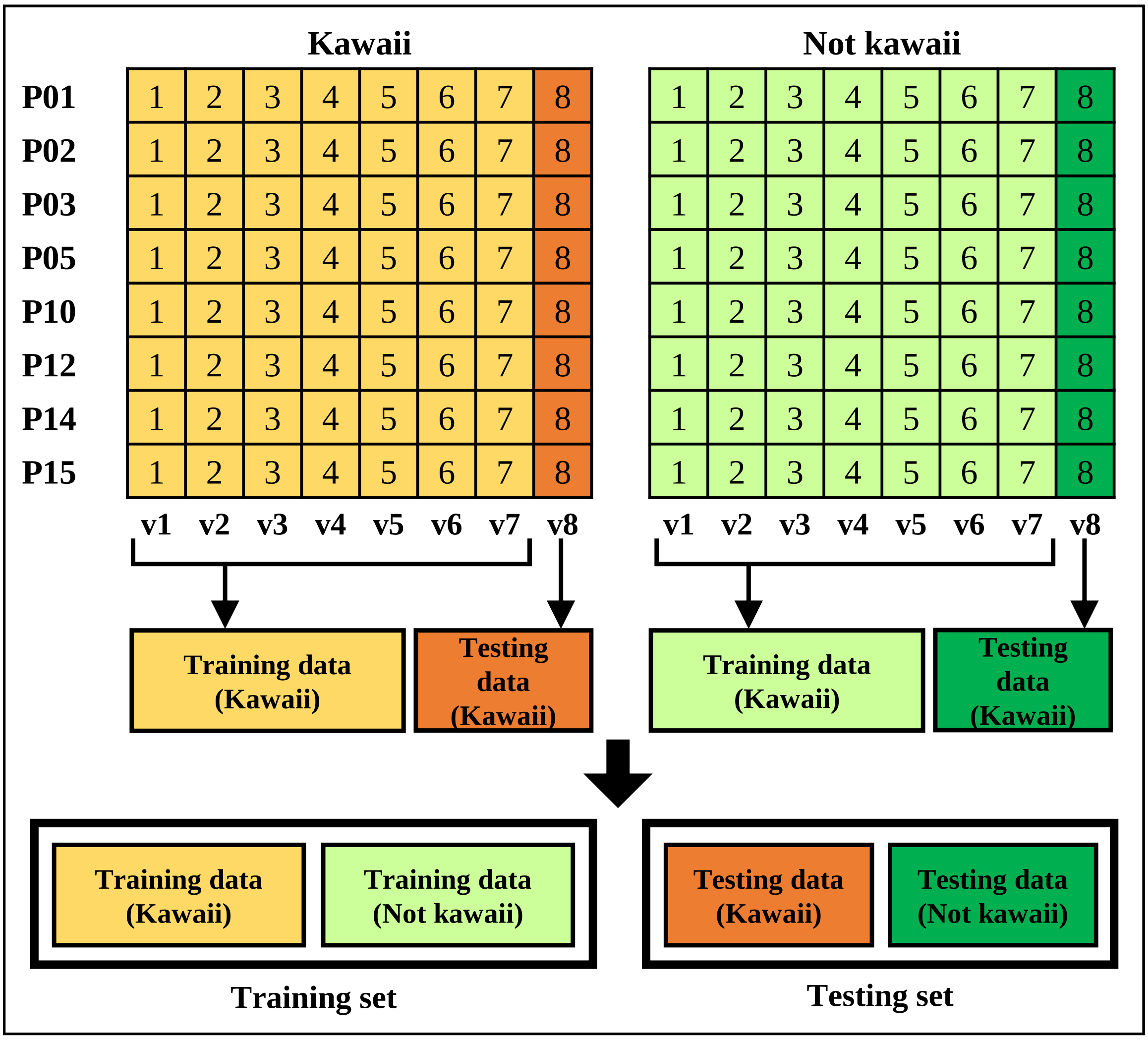



**Figure 7.4** Steps to prepare training and testing sets

For Japanese participants, I used the evaluation results of 11 participants from the previous step as the dataset. It consisted of 11,528 images that were classified into kawaii (5,354 images) and not-kawaii (6,174 images) groups.

By using the same method as that of Thai participants, I prepared the dataset for k-fold cross validation (k=11). Therefore, the dataset was divided into 11 subsets (11 different training and testing sets). The reason that I changed the number of folds (k) was that equal numbers between the folds (k) and subsets for the cross validation can ensure that all 1,048 images equally appear once in every subset.

#### 7.3.1.2 Model Training

From the data preparation step, I obtained the two datasets: dataset of Thai participants, and that of Japanese participants. For dataset of Thai participants, I used eight training sets to train eight different models for cross validation. Similarly, for dataset of Japanese participants, I used 11 training sets to train 11 different models.

To select appropriate Deep CNN algorithm for model training, I performed the performance test of five kinds of CNN algorithms: Network in Network, AlexNet, AlexNet with Batch Normalization, GoogLeNet, and GoogLeNet with Batch Normalization. I employed only a dataset containing the result of one Thai participant as input to train models using those five algorithms. Then, I tested their performance indicating by classification accuracy. The result of performance test is shown in **Table 7.3**.

**Table 7.3** Result of performance test among five kinds of CNN algorithms

| Algorithm | Accuracy (%) |
|---|---|
| Network in Network | 67 |
| AlexNet | 72 |
| AlexNet with Batch Normalization | 63 |
| GoogLeNet | 57 |
| GoogLeNet with Batch Normalization | 74 |

From the result of performance test, AlexNet and GoogLeNet with Batch Normalization performed best in term of accuracy. However, by observing the prediction results, GoogLeNet with Batch Normalization performed quite better that the classification probabilities were almost either 0 or 1, while those of AlexNet were around 0.5. Based on this observation, I assumed that GoogLeNet with Batch Normalization performed best in both accuracy and the classification performance into binary classes (kawaii or not kawaii). Therefore, this algorithm was selected to train the models in further steps.

The following are the parameter settings for training the models using GoogLeNet with Batch Normalization algorithm.

- Training settings:
  - Epoch: 50
  - Batch size: 64
  - Learning rate: 0.01
- Image preprocessing settings:
  - Color mode: RGB
  - Image resizing method: Squash
  - Image flipping: Yes

#### 7.3.1.3 Model Validation

I performed eight-fold cross-validation using eight trained models from the previous step as testing data that correspond to each model.

To determine whether each image was correctly classified by the model, I set a cutoff value (or classification probability) at 50%, which is the default value for a binary classifier. For example, if the probability of an image in the kawaii group is greater than 50%, it is classified as kawaii. On the other hand, any images with a classification probability less than 50% are classified as not kawaii.

For each model, I created confusion matrix (Figure 7.5) which is often used to describe the performance of a classification model. I calculated 3 performance metrics. Formula to calculate and interpretation of each metric are shown as follows:

- Accuracy = (TP+TN) / (TP+TN+FP+FN) ;
  Ability to differentiate between kawaii and not-kawaii
- Sensitivity = TP / (TP+FN) ;
  Ability to determine kawaii case correctly
- Specificity = TN / (TN + FP) ;
  Ability to determine not-kawaii case correctly

| | | Actual Condition | |
|---|---|---|---|
| | | **Kawaii** | **Not-kawaii** |
| **Predicted Condition** | **Kawaii** | True Positive (TP) | False Positive (FP) |
| | **Not-kawaii** | False Negative (FN) | True Negative (TN) |

**Figure 7.5** Confusion matrix

### 7.3.2 Results of Model Construction

For the results of Thai dataset (Table 7.4), all three performance metrics were in certain ranges, which indicates its consistency. This result ensured that the robustness to construct a final model using this dataset.

For the results of Japanese dataset (Table 7.5), even though the ranges of sensitivity and specificity had variability, the range of accuracy had consistency which was similar to that of Thai participants.

**Table 7.4** Classification Results of All Models of Thai Participants

| **Model No.** | **Number of correctly classified images / Number of all images to be classified** | | **Accuracy (%)** | **Sensitivity (%)** | **Specificity (%)** |
|---|---|---|---|---|---|
| | **Kawaii** | **Not kawaii** | | | |
| 1 | 255 / 507 | 398 / 542 | 62 | 50 | 73 |
| 2 | 265 / 507 | 417 / 541 | 65 | 52 | 77 |
| 3 | 262 / 506 | 402 / 542 | 63 | 52 | 74 |
| 4 | 276 / 506 | 399 / 542 | 64 | 55 | 74 |
| 5 | 268 / 506 | 422 / 542 | 66 | 52 | 78 |
| 6 | 246 / 506 | 423 / 542 | 64 | 49 | 78 |
| 7 | 280 / 506 | 384 / 541 | 63 | 55 | 71 |
| 8 | 250 / 506 | 407 / 541 | 63 | 49 | 75 |

**Table 7.5** Classification Results of All Models of Japanese Participants

| Model No. | Number of correctly classified images / Number of all images to be classified | | Accuracy (%) | Sensitivity (%) | Specificity (%) |
|---|---|---|---|---|---|
| | Kawaii | Not kawaii | | | |
| 1 | 277 / 487 | 399 / 562 | 64 | 57 | 71 |
| 2 | 268 / 487 | 393 / 562 | 63 | 55 | 70 |
| 3 | 303 / 487 | 357 / 562 | 63 | 62 | 64 |
| 4 | 253 / 487 | 435 / 561 | 66 | 52 | 78 |
| 5 | 207 / 487 | 454 / 561 | 63 | 43 | 81 |
| 6 | 235 / 487 | 424 / 561 | 63 | 48 | 76 |
| 7 | 170 / 487 | 472 / 561 | 61 | 35 | 84 |
| 8 | 255 / 487 | 407 / 561 | 63 | 52 | 73 |
| 9 | 288 / 486 | 369 / 561 | 63 | 59 | 66 |
| 10 | 212 / 486 | 463 / 561 | 64 | 44 | 83 |
| 11 | 200 / 486 | 461 / 561 | 63 | 41 | 82 |

Since the classification results showed a certain consistency, I constructed 2 final models for Thai and Japanese dataset. For each of them, all balanced data were used as input. Finally, I obtained a final model for Thai participants, and the other final model for Japanese participants. They were used in the next step to evaluate the kawaiiness of cosmetic bottles.

### 7.3.3 Discussion

The result of model construction (Section 7.3.2) indicates that I successfully constructed the models of kawaii feelings for cosmetic bottles using CNN algorithm [99]. Therefore, I confirmed that the limitation of SVM algorithm in feature extraction was solved by using the Deep CNN algorithm.

However, since this was the first trial on model construction using CNN algorithm, the model performance has not been considered yet. The models were constructed separately for only Thai or Japanese dataset. Therefore, the similarities and differences among nationalities, genders, and generations, have not been taken into account yet. In addition, the models still need the optimization to increase the performance. Below are future possibilities to increase the performance of the models:

- Analyzing the similarities and differences among nationalities, genders, and generations to prepare appropriate dataset for model construction

- Modifying the architecture of Deep CNN algorithm to include demographic information of participants (e.g. nationalities, genders, and generations) as additional parameters to train the models
- Employing other Deep CNN algorithms and optimizing their parameters
- Increasing the fully connected layers of the Deep CNN architecture
- Using simple CNN algorithm and visualize the convolutional layers to support the result of kawaii attributes

## 7.4 Evaluation of Attributes of Cosmetic Bottles using Model

### 7.4.1 Evaluation Procedure

The procedure for evaluating the kawaiiness of the cosmetic bottle images is described as follows:

1. Collection of cosmetic bottle images: The images that all the participants agreed as kawaii and not kawaii were used for evaluation.

2. Attribute observation: I observed the tendency of the kawaii attributes of the images collected from the step 1) and made an assumption about which attributes are likely to be effective for kawaiiness.

3. Evaluation of attributes using models: I modified the original images based on our assumption and applied the final models to evaluate the kawaii probabilities of both the original and modified images. Then I calculated the difference of the kawaii probabilities between the original and modified images to confirm the assumption.

### 7.4.2 Evaluation Results and Discussion

#### 7.4.2.1 Results of collection of cosmetic bottle images

For Thai dataset, I collected cosmetic bottle images that all eight participants agreed as kawaii (43 images) and those that were not kawaii (40 images). Note that some images were excluded due to misclassification by the model.

For Japanese dataset, I also collected cosmetic bottle images that all 11 participants agreed as kawaii (10 images) and those that were not kawaii (27 images). This result shows that Japanese participants had more variety in the evaluation of kawaiiness for cosmetic bottles than Thai participants.

#### 7.4.2.2 Results of attribute observation

For both results of Thai and Japanese participants, there were variety of cap ornamentation of the images in kawaii groups. In contrary, there were mostly no objects on cap ornamentation of those in not-kawaii group. Therefore, I made the following assumption: the kawaii caps are effective attributes to increase kawaiiness.

Since such objects as ribbons and flowers are generally known as kawaii objects, I divided the images by focusing on these two objects. Therefore, the images were divided into four groups based on the objects on bottle caps.

1. Ribbons
2. Flowers
3. Other objects (leaves, butterfly, hat, etc.)
4. No objects or ordinary caps

The results for Thai and Japanese datasets are shown in Table 7.6 and Table 7.7 respectively.

**Table 7.6** Cosmetic Bottle Images Grouped by Objects on Bottle Caps for Thai Participants

| Group of Cosmetic Bottle Image | Number of images | |
|---|---|---|
| | Kawaii | Not kawaii |
| Ribbon | 11 | 0 |
| Flower | 10 | 0 |
| Other | 14 | 0 |
| No objects | 8 | 40 |

**Table 7.7** Cosmetic Bottle Images Grouped by Objects on Bottle Caps for Japanese Participants

| **Group of Cosmetic Bottle Image** | **Number of images** | |
|---|---|---|
| | **Kawaii** | **Not kawaii** |
| Ribbon | 4 | 0 |
| Flower | 1 | 0 |
| Other | 1 | 2 |
| No objects | 4 | 25 |

#### 7.4.2.3 Results of evaluation of attributes using models

To prove the assumption, I modified the images by removing their bottle caps. Thus, I obtained two sets of images: with bottle caps (original images) and without bottle caps (modified images). Next I evaluated the kawaiiness of these two sets using the model of Thai and Japanese participants separately.

As shown in Figure 7.6, I used cosmetic bottle images with and without caps as the model's input. The output of the model of each image was the probabilities of classification into kawaii and not-kawaii groups. I calculated the difference of the kawaii probabilities of the cosmetic bottle images with and without caps. This value indicates the effect of the bottle caps on the kawaiiness of each cosmetic bottle image.

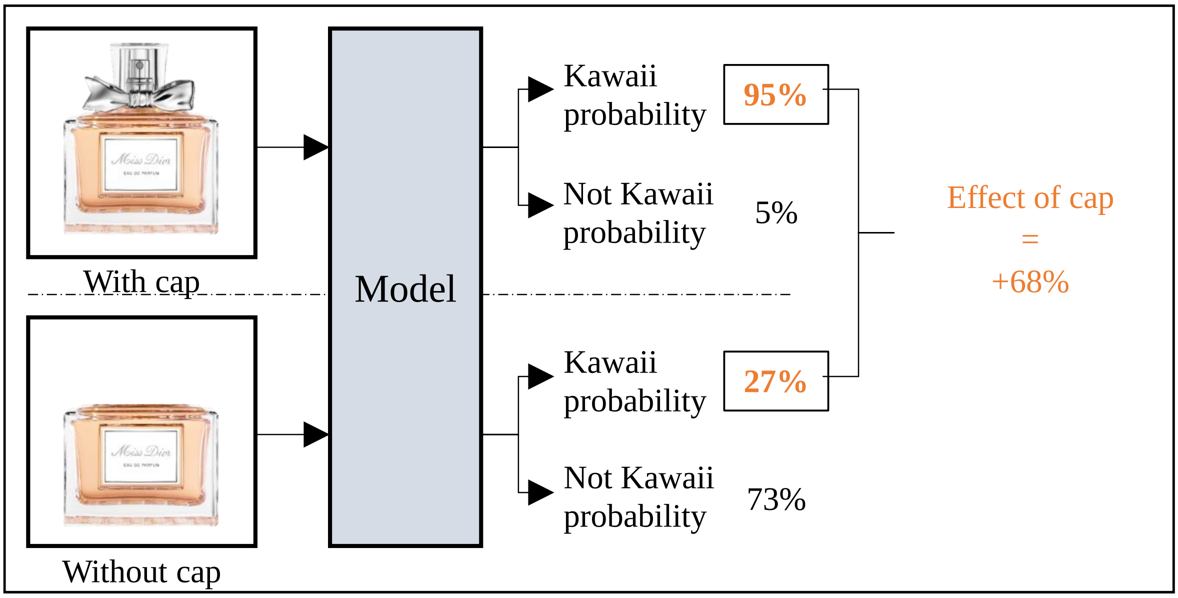



**Figure 7.6** Method to calculate difference of kawaii probabilities between cosmetic bottle images with/without caps

Next I calculated the mean difference of kawaii probabilities for each group of cosmetic bottle images. Then I performed independent-samples t-tests for the statistically significant mean difference between two groups of cosmetic bottle images.

For Thai dataset, the results (Figure 7.7) are described as follows:

- The mean differences of the kawaii probabilities between the not-kawaii group and each of the groups of kawaii images were significantly different with $p<0.01$. These results indicate that the kawaii caps had a larger effect on kawaiiness than the not-kawaii caps.
- The mean differences of the kawaii probabilities between the groups with ribbons and no objects were significantly different with $p<0.05$, and that of other objects was significantly different with $p<0.1$. This result indicates that ribbon caps had a larger effect on kawaiiness than caps with other objects or no objects among the kawaii images.
- There were no significant differences between the groups with ribbons and flowers. This result indicates that the kawaii caps, especially ribbons and flowers, effectively increased the kawaiiness of cosmetic bottles.

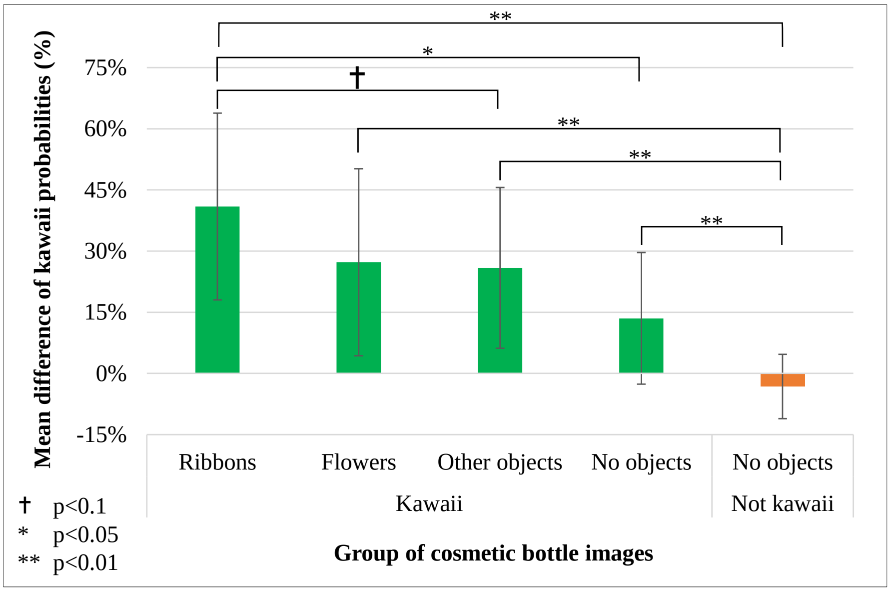



**Figure 7.7** Mean difference of kawaii probabilities among cosmetic bottle images grouped by objects on the bottle caps for Thai participants

For the results of Japanese datasets (Figure 7.8), the mean difference of the kawaii images with ribbons was the largest (29.3%), while those of other groups were small. However, the independent-samples t-tests did not show any statistically significant mean differences between any two groups of cosmetic bottle images. Therefore, I obtained only the tendency that ribbons are likely to increase the kawaiiness of cosmetic bottles.

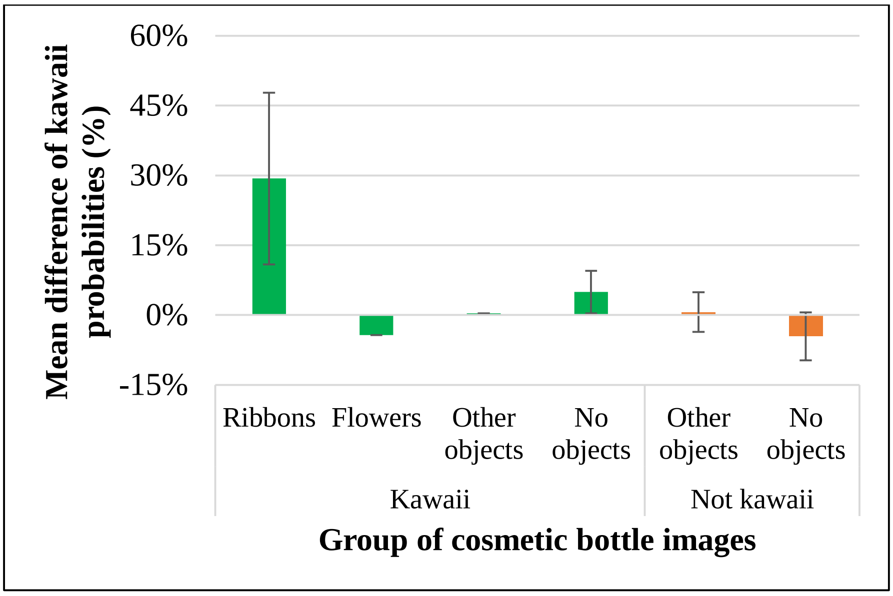



**Figure 7.8** Mean difference of kawaii probabilities among cosmetic bottle images grouped by objects on the bottle caps for Japanese participants

These results resembled previous experiment (Chapter 5, Chapter 6, and Chapter 7) that such objects as flowers were effective attributes for the kawaiiness of products. In addition, the small difference of kawaii probabilities for the images with no objects indicated that simply removing caps did not always lead to the decrease of kawaiiness.

In Section 7.4, I employed the constructed model obtained from Section 7.3 to evaluate the kawaiiness of cosmetic bottles. Since Deep CNN model cannot generate the candidates of effective attributes as done by SVM model, I used a new method to obtain those attributes by modify images based on particular attributes and use the Deep CNN model to predict the kawaii probabilities. Therefore, I confirmed that the limitation of Deep CNN algorithm was solved. In addition, the model effectively used to evaluate bottle caps as candidates of effective attributes, which shows that Deep CNN model can use not only for evaluation of total impression, but also for evaluation of particular attributes.

As the results, I developed a new method to evaluate candidates of attributes using the Deep CNN model. However, there are still many other methods that can also be employed for the evaluation. One example is to use the model to evaluate only one part of the cosmetic bottles to confirm that such part is really important for the kawaiiness or not. If the model outputs high kawaii probability, such part might be concluded as kawaii. However, if it is not kawaii without the combination with other parts, the kawaii probability might be less. This and other methods remains as future work.

## 7.5 Relationship among Physical Attributes of Cosmetic Bottles, Model, and Eye Movements Caused by Kawaii Feelings

From previous step, I evaluated the candidates of effective attributes for kawaii cosmetic bottles based on the predicted results by the model. In this step, I experimentally clarified the effective attributes using eye tracking [100]. The objectives were as follows:

1. To confirm the usefulness of eye movement indexes from previous experiment
2. To clarify the relationship between physical attributes of cosmetic bottles, predicted results by the model, and eye movement indexes, caused by kawaii feelings
3. To clarify the effective attributes to increase kawaiiness of cosmetic bottles for Japanese participants

### 7.5.1 Experiment Method

#### 7.5.1.1 Observation of Attributes

To select the candidates of attributes for kawaii cosmetic bottles, I observed the images that 10 or 11 Japanese participants agreed as kawaii or not-kawaii from the data collection result in previous step. In this experiment, I needed to employ the result of 10 participants because the number of images from that of 11 participants was too few to observe the tendency. Therefore, the images I used for the observation of attributes were divided into kawaii group (67 images that 10 or 11 participants agreed as kawaii) and not-kawaii group (29 images that 11 participants agreed as not kawaii).

The observation was performed to make an assumption about the attributes for kawaii cosmetic bottles. I compared the tendency of attributes between kawaii and not-kawaii groups. Based on the tendency of attributes, I selected three candidates of attributes for this experiment as described next.

### A. Cap Ornamentation

From the observation of images in kawaii group, there were 11 images with flowers and 11 images with ribbons as cap ornamentation. Since I considered that the balance of hues between caps and bottles were necessary to keep the overall impression, I employed the original caps and the original hues for the bottles. Based on hues, I divided the cosmetic bottle images into 5 groups: monochrome, blue, pink, green and yellow. Finally, I selected the 10 candidates of cap ornamentation (Table 7.8) based on the following conditions.

1. To keep the balance in size for further eye movement analysis, caps with too large size were excluded.
2. Some caps had similar flowers or ribbons. Only one of them was selected.
3. I selected caps that had both flower and ribbon candidates. Therefore, green and yellow images were excluded because they had no ribbon caps.

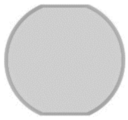
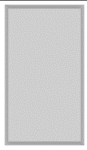
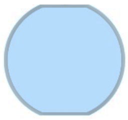
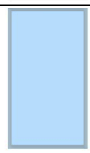
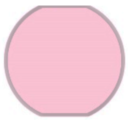
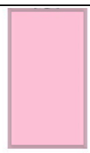
**Table 7.8** Cosmetic bottle images used as candidates of cap ornamentation

| **Hue** | **Cap Ornamentation** | | | |
|---|---|---|---|---|
| | **Flower** | | **Ribbon** | |
| Monochrome |  F1 |  F2 |  R1 |  R2 |
| Blue |  F3 | |  R3 | |
| Pink |  F4 |  F5 |  R4 |  R5 |

### B. Bottle Shape

From the observation of bottle shapes, the images in kawaii group tended to have round bottles, while those of not-kawaii group tended to have square bottles. Based on this tendency, I selected two different bottle shapes, round and square, as shown in Table 7.9.

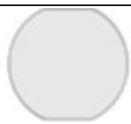
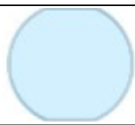
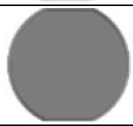
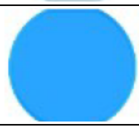
**Table 7.9** Two bottle shapes of each hue

| **Hue** | **Bottle Shape** | |
|---|---|---|
| | **Round** | **Square** |
| Monochrome |  |  |
| Blue |  |  |
| Pink |  |  |

### C. Bottle Lightness/Saturation (L/S)

From the observation of bottle lightness/saturation, the images in kawaii group tended to have transparent bottles which were related to the low values of lightness and saturation. In contrary, those of not-kawaii tended to have black or solid colors which were related to the high values of lightness and saturation. Based on this tendency, I set three levels of lightness/saturation (dark, bright, and brilliant) by adjusting the combination of lightness and saturation as shown in Table 7.10.

**Table 7.10** Three levels of lightness/saturation of each hue

| Level | Lightness | Saturation | Hue | | |
|---|---|---|---|---|---|
| | | | Monochrome | Blue | Pink |
| 1 (Dark) | 0 | 0 |  |  |  |
| 2 (Bright) | -15 | 50 |  |  |  |
| 3 (Brilliant) | -30 | 100 |  |  |  |

### 7.5.1.2 Candidates of Cosmetic Bottle Images

From the observation result of cap ornamentation, I employed only caps of the 10 images. Then, I modified their bottle shapes and bottle lightness/saturation based on their original hues. As a result, the total number of modified images was 60 images (24 monochrome, 12 blue, and 24 pink hues) as shown in Table 7.11.

### 7.5.1.3 Comparison System

I modified the comparison system from previous experiments. The system used 60 modified images as visual stimuli. For this experiment, I compared the images among the same hues only. For each hue, they were displayed in pairs. The total number of compared pairs was 60 times (24 times for monochrome, 12 times for blue, 24 times for pink). The order of compared pairs was shuffled to avoid the same hues and images between two consecutive pairs.

All combinations of compared pairs divided by hues are shown in Table 7.12. For each pair of comparison, all three attributes were different. For example, the first pair (top left) was the comparison between images #1 and #17 in which their attributes were {*F1 (flower)* Cap, *Round* Shape, Lightness/Saturation Level *1*} and {*R1 (ribbon)* Cap, *Square* Shape, Lightness/Saturation Level *2*} respectively.

**Table 7.11** All modified cosmetic bottle images

| **Hue** | **Attribute** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **Cap ID (Cap)** | **Shape = Round** | | | **Shape = Square** | | |
| | | **L/S = 1** | **L/S = 2** | **L/S = 3** | **L/S = 1** | **L/S = 2** | **L/S = 3** |
| **Monochrome** | **F1 (Flower)** | #1 | #2 | #3 | #4 | #5 | #6 |
| | **F2 (Flower)** | #7 | #8 | #9 | #10 | #11 | #12 |
| | **R1 (Ribbon)** | #13 | #14 | #15 | #16 | #17 | #18 |
| | **R2 (Ribbon)** | #19 | #20 | #21 | #22 | #23 | #24 |
| **Blue** | **F3 (Flower)** | #25 | #26 | #27 | #28 | #29 | #30 |
| | **R3 (Ribbon)** | #31 | #32 | #33 | #34 | #35 | #36 |
| **Pink** | **F4 (Flower)** | #37 | #38 | #39 | #40 | #41 | #42 |
| | **F5 (Flower)** | #43 | #44 | #45 | #46 | #47 | #48 |
| | **R4 (Ribbon)** | #49 | #50 | #51 | #52 | #53 | #54 |
| | **R5 (Ribbon)** | #55 | #56 | #57 | #58 | #59 | #60 |

**Table 7.12** Combination of compare pairs of cosmetic bottle images divided by hues

| | **F1** | **Image ID** | **R1** | **Image ID** | **F1** | **Image ID** | **R2** | **Image ID** |
|---|---|---|---|---|---|---|---|---|
| Monochrome | ○1 | #1 | □2 | #17 | ○1 | #1 | □3 | #24 |
| | ○2 | #2 | □3 | #18 | ○2 | #2 | □1 | #22 |
| | ○3 | #3 | □1 | #16 | ○3 | #3 | □2 | #23 |
| | □1 | #4 | ○3 | #15 | □1 | #4 | ○2 | #20 |
| | □2 | #5 | ○1 | #13 | □2 | #5 | ○3 | #21 |
| | □3 | #6 | ○2 | #14 | □3 | #6 | ○1 | #19 |
| | **F2** | **Image ID** | **R1** | **Image ID** | **F2** | **Image ID** | **R2** | **Image ID** |
| | ○1 | #7 | □3 | #18 | ○1 | #7 | □2 | #23 |
| | ○2 | #8 | □1 | #16 | ○2 | #8 | □3 | #24 |
| | ○3 | #9 | □2 | #17 | ○3 | #9 | □1 | #22 |
| | □1 | #10 | ○2 | #14 | □1 | #10 | ○3 | #21 |
| | □2 | #11 | ○3 | #15 | □2 | #11 | ○1 | #19 |
| | □3 | #12 | ○1 | #13 | □3 | #12 | ○2 | #20 |
| Blue | **F3** | **Image ID** | **R3** | **Image ID** | **F3** | **Image ID** | **R3** | **Image ID** |
| | ○1 | #25 | □2 | #35 | ○1 | #25 | □3 | #36 |
| | ○2 | #26 | □3 | #36 | ○2 | #26 | □1 | #34 |
| | ○3 | #27 | □1 | #34 | ○3 | #27 | □2 | #35 |
| | □1 | #28 | ○3 | #33 | □1 | #28 | ○2 | #32 |
| | □2 | #29 | ○1 | #31 | □2 | #29 | ○3 | #33 |
| | □3 | #30 | ○2 | #32 | □3 | #30 | ○1 | #31 |
| Pink | **F4** | **Image ID** | **R4** | **Image ID** | **F4** | **Image ID** | **R5** | **Image ID** |
| | ○1 | #37 | □2 | #53 | ○1 | #37 | □3 | #60 |
| | ○2 | #38 | □3 | #54 | ○2 | #38 | □1 | #58 |
| | ○3 | #39 | □1 | #52 | ○3 | #39 | □2 | #59 |
| | □1 | #40 | ○3 | #51 | □1 | #40 | ○2 | #56 |
| | □2 | #41 | ○1 | #49 | □2 | #41 | ○3 | #57 |
| | □3 | #42 | ○2 | #50 | □3 | #42 | ○1 | #55 |
| | **F5** | **Image ID** | **R4** | **Image ID** | **F5** | **Image ID** | **R5** | **Image ID** |
| | ○1 | #43 | □3 | #54 | ○1 | #43 | □2 | #59 |
| | ○2 | #44 | □1 | #52 | ○2 | #44 | □3 | #60 |
| | ○3 | #45 | □2 | #53 | ○3 | #45 | □1 | #58 |
| | □1 | #46 | ○2 | #50 | □1 | #46 | ○3 | #57 |
| | □2 | #47 | ○3 | #51 | □2 | #47 | ○1 | #55 |
| | □3 | #48 | ○1 | #49 | □3 | #48 | ○2 | #56 |

***Note*** Cap ID is denoted by F~ (flower) and R~ (ribbon)
Shape is denoted by ○ (round) and □ (square)
Lightness/Saturation is denoted by 1 (dark), 2 (bright), and 3 (brilliant)

The structure of the comparison system is described as follows:

1. Top page: questionnaire explanation
2. Consent form: brief explanation about experiment and permission to use their data
3. Explanation of cosmetic bottle image selections
4. Cosmetic bottle images comparison:
    a. A cross sign (+) appeared at the middle of the display for 2.5 seconds to fix the eyes at the same position before each comparison.
    b. The pairs of cosmetic bottle images were randomly displayed with a 5-second countdown timer. Selections of more kawaii ones were performed using the keyboard's left or right arrow keys. (Figure 7.9)
5. Questionnaire: Criteria for selecting kawaii cosmetic bottle images (free description) was asked.
6. Last page: the system explained that the comparison was finished.
7. The selection and questionnaire results were saved in a database.

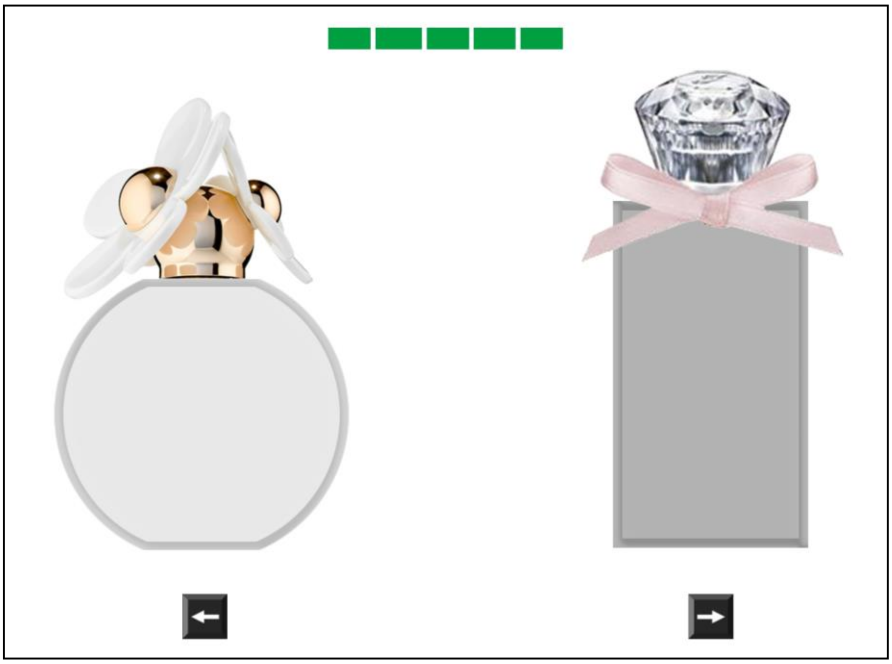


**Figure 7.9** Screenshot of comparison system displaying two cosmetic bottle images and countdown timer

#### 7.5.1.4 Experimental Setup and Procedure

The experimental setup of this chapter was the same as previous experiments that used the comparison system with eye tracking system (Chapters 3 and 6). The comparison system was accessed from the eye tracking system through a web browser. The eye tracking system and the monitor were the same as in previous experiments.

The following are the experimental procedures:

1. Participant sat on chairs in front of the PC.
2. Participant read the explanation of the experiment.
3. Experimenter calibrated the eyes of the participant.
4. Experimenter showed the comparison system and started recording eye movements.
5. Participant selected more kawaii cosmetic bottle images from 60 pairs.
6. Participant answered the questionnaire.
7. Experimenter stopped recording the eye movements.

### 7.5.2 Experimental Results

#### 7.5.2.1 Participants

Since females usually have more interest in cosmetic bottles than males, I recruited only female participants for this experiment. The experiment was performed with 14 Japanese female volunteers, all of whom were university students in their 20’s. However, only 10 bits of eye tracking data were successfully collected.

#### 7.5.2.2 Cumulative Results

I collected the cumulative results (the kawaii scores) from the selection results of each participant. For each participant, each of the images in each hue has maximum score at 2, which means that each image appears for 2 times equally. For monochrome group, the total scores were 24, as well as pink group. For blue group, the total score was 12. Then, I calculated the average scores of each image from the scores of all participants. Finally, I normalized the scores of all images into percentage. The results are shown in Table 7.13.

Based on the average score, the most kawaii image for monochrome was #8, for blue was #32, and for pink was #38 (Figure 7.10). All of them had round bottle shapes and level 2 (bright) of lightness/saturation. On the other hand, the least kawaii image for monochrome was #18, for blue was #30, and for pink was #52 (Figure 7.11). All of them had square bottle shape.

**Table 7.13** Average scores of all cosmetic bottle images divided by hues

| Monochrome | | Blue | | Pink | |
|---|---|---|---|---|---|
| **Image ID** | **Average Score (%)** | **Image ID** | **Average Score (%)** | **Image ID** | **Average Score (%)** |
| #1 | 60.71 | #25 | 42.86 | #37 | 67.86 |
| #2 | 53.57 | #26 | 53.57 | #38 | 85.71 |
| #3 | 53.57 | #27 | 28.57 | #39 | 67.86 |
| #4 | 46.43 | #28 | 32.14 | #40 | 67.86 |
| #5 | 57.14 | #29 | 50.00 | #41 | 75.00 |
| #6 | 42.86 | #30 | 17.86 | #42 | 60.71 |
| #7 | 60.71 | #31 | 67.86 | #43 | 71.43 |
| #8 | 75.00 | #32 | 78.57 | #44 | 78.57 |
| #9 | 57.14 | #33 | 53.57 | #45 | 60.71 |
| #10 | 50.00 | #34 | 60.71 | #46 | 67.86 |
| #11 | 46.43 | #35 | 67.86 | #47 | 57.14 |
| #12 | 53.57 | #36 | 46.43 | #48 | 46.43 |
| #13 | 50.00 | | | #49 | 46.43 |
| #14 | 53.57 | | | #50 | 39.29 |
| #15 | 42.86 | | | #51 | 21.43 |
| #16 | 50.00 | | | #52 | 17.86 |
| #17 | 42.86 | | | #53 | 35.71 |
| #18 | 32.14 | | | #54 | 25.00 |
| #19 | 46.43 | | | #55 | 46.43 |
| #20 | 60.71 | | | #56 | 39.29 |
| #21 | 50.00 | | | #57 | 32.14 |
| #22 | 35.71 | | | #58 | 28.57 |
| #23 | 39.29 | | | #59 | 39.29 |
| #24 | 39.29 | | | #60 | 21.43 |

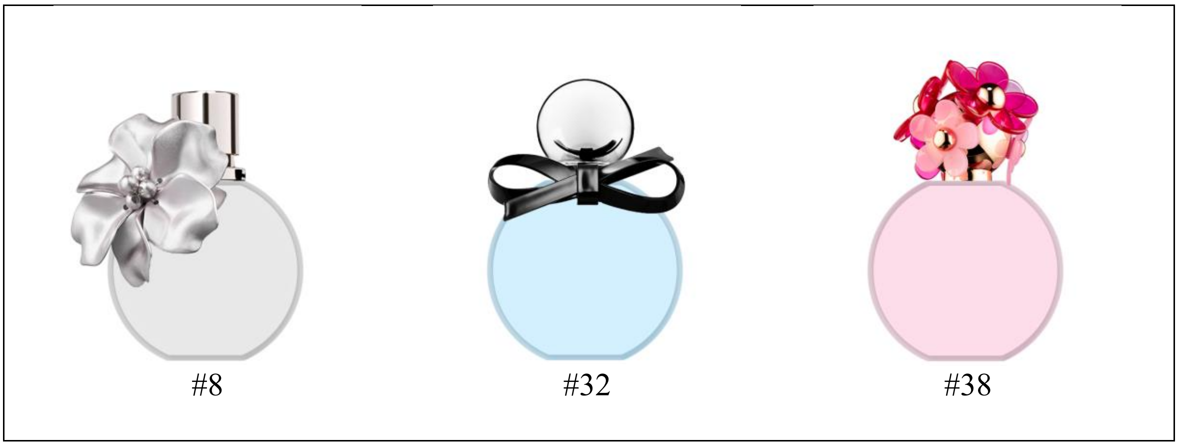



**Figure 7.10** The most kawaii cosmetic bottle images based on average scores divided by hues

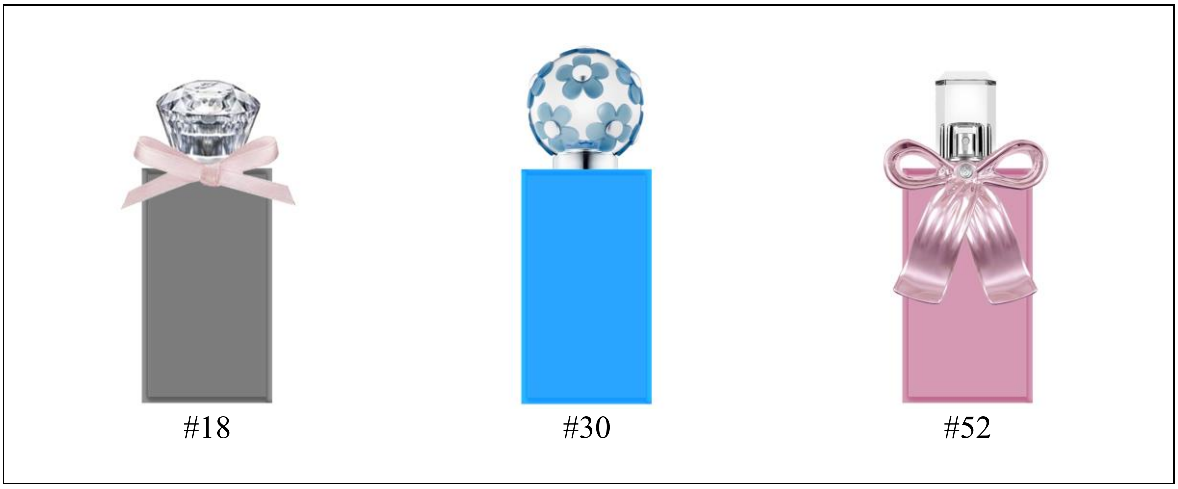



**Figure 7.11** The least kawaii cosmetic bottle images based on average scores divided by hues

Next, I analyzed the effects of the three attributes for each hue using three-factor ANOVA. Then, I performed Tukey's post hoc tests to confirm the differences between groups of each attribute (Figure 7.12, Figure 7.13, Figure 7.14). For each hue, the analyzed results are described as follows:

### A. Monochrome images

From the results of three-factor ANOVA, there were statistically significant main effects of caps ($p<0.05$) and shapes ($p<0.05$). However, the results did not show statistically significant main effect of lightness/saturation and any interaction effects. The results indicated that caps and shapes were effective attributes for kawaii monochrome cosmetic bottle images.

**Table 7.14** Results of 3-factor ANOVA for monochrome images

| Attribute | Sum of Squares | DF | Mean Square | F | P-value |
|---|---|---|---|---|---|
| **Cap** | 3.048 | 1 | 3.048 | 4.265 | 0.040* |
| **Shape** | 3.857 | 1 | 3.857 | 5.398 | 0.021* |
| **L/S** | 1.143 | 2 | 0.571 | 0.800 | 0.450 |
| **Cap x Shape** | 0.000 | 1 | 0.000 | 0.000 | 1.000 |
| **Cap x L/S** | 0.024 | 2 | 0.012 | 0.017 | 0.983 |
| **Shape x L/S** | 0.214 | 2 | 0.107 | 0.150 | 0.861 |
| **Cap x Shape x L/S** | 0.214 | 2 | 0.107 | 0.150 | 0.861 |
| **Error** | 231.500 | 324 | 0.715 | | |
| **Total** | 576.000 | 336 | | | |

From the results of Tukey's post hoc tests, there were statistically significant differences between caps ($p<0.05$) and shapes ($p<0.05$) which indicated the following results.

- Caps: flower > ribbon
- Shape: round > square

**B. Blue images**

From the results of three-factor ANOVA, there were statistically significant main effects of cap ($p<0.01$) and lightness/saturation ($p<0.01$). However, the results did not show statistically significant main effect of shape and any interaction effects. The results indicated that caps and lightness/saturation were effective attributes for kawaii blue cosmetic bottle images.

**Table 7.15** Results of 3-factor ANOVA for blue images

| Attribute | Sum of Squares | DF | Mean Square | F | P-value |
|---|---|---|---|---|---|
| **Cap** | 19.429 | 11 | 1.766 | 2.538 | 0.000** |
| **Shape** | 168.000 | 1 | 168.000 | 241.389 | 0.197 |
| **L/S** | 10.500 | 1 | 10.500 | 15.087 | 0.005** |
| **Cap x Shape** | 1.167 | 1 | 1.167 | 1.676 | 1.000 |
| **Cap x L/S** | 7.536 | 2 | 3.768 | 5.414 | 0.926 |
| **Shape x L/S** | 0.000 | 1 | 0.000 | 0.000 | 0.991 |
| **Cap x Shape x L/S** | 0.107 | 2 | 0.054 | 0.077 | 0.926 |
| **Error** | 0.012 | 2 | 0.006 | 0.009 | |
| **Total** | 0.107 | 2 | 0.054 | 0.077 | |

From the results of Tukey's post hoc tests, there were statistically significant differences between caps ($p<0.01$) and lightness/saturation ($p<0.05$) which indicated the following results.

- Caps: ribbon > flower
- Lightness/saturation: level 2 (bright) > level 3 (brilliant)

**C. Pink images**

From the results of three-factor ANOVA, there were statistically significant main effects of caps ($p<0.01$), shapes ($p<0.05$), and lightness/saturation ($p<0.05$). However, the results did not show any statistically significant interaction effects. The results indicated that caps and shapes were effective attributes for kawaii pink cosmetic bottle images.

**Table 7.16** Results of 3-factor ANOVA for pink images

| Attribute | Sum of Squares | DF | Mean Square | F | P-value |
|---|---|---|---|---|---|
| **Cap** | 50.071 | 11 | 4.552 | 7.162 | 0.000** |
| **Shape** | 336.000 | 1 | 336.000 | 528.649 | 0.029* |
| **L/S** | 40.048 | 1 | 40.048 | 63.009 | 0.024* |
| **Cap x Shape** | 3.048 | 1 | 3.048 | 4.795 | 1.000 |
| **Cap x L/S** | 4.786 | 2 | 2.393 | 3.765 | 0.981 |
| **Shape x L/S** | 0.000 | 1 | 0.000 | 0.000 | 0.877 |
| **Cap x Shape x L/S** | 0.024 | 2 | 0.012 | 0.019 | 0.209 |
| **Error** | 0.167 | 2 | 0.083 | 0.131 | |
| **Total** | 2.000 | 2 | 1.000 | 1.573 | |

From the results of Tukey's post hoc tests, there were statistically significant differences between caps ($p<0.01$), shapes ($p<0.05$) and lightness/saturation ($p<0.05$), which indicated the following results.

- Caps: ribbon > flower
- Shape: round > square
- Lightness/saturation: level 2 (bright) > level 3 (brilliant)

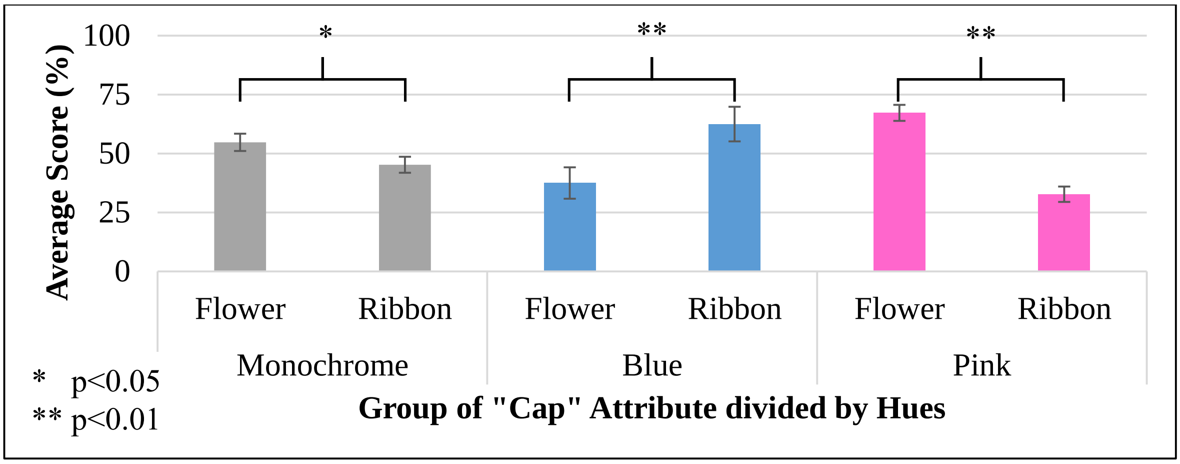



**Figure 7.12** Average scores between flower and ribbon as "cap" attribute divided by hues

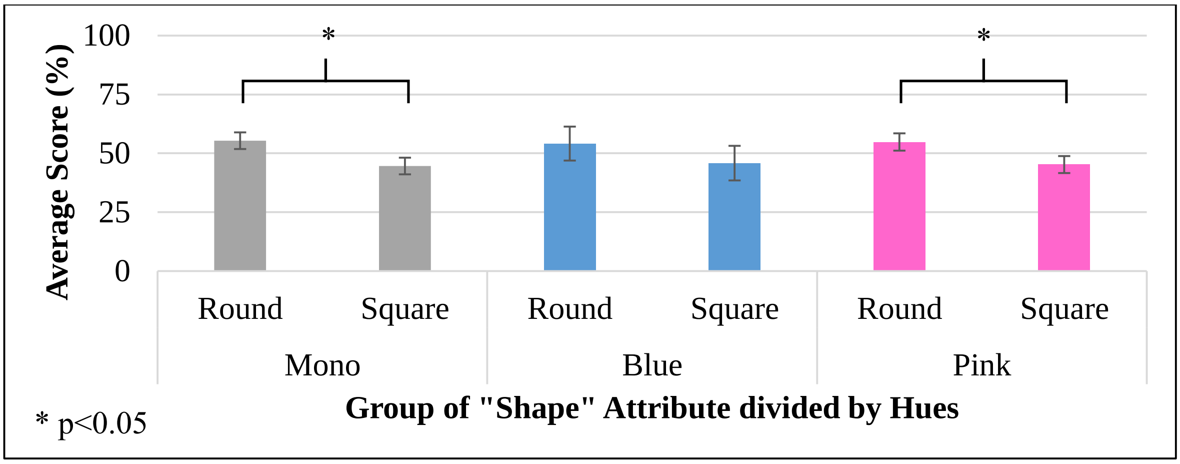



**Figure 7.13** Average scores between round and square as "shape" attribute divided by hues

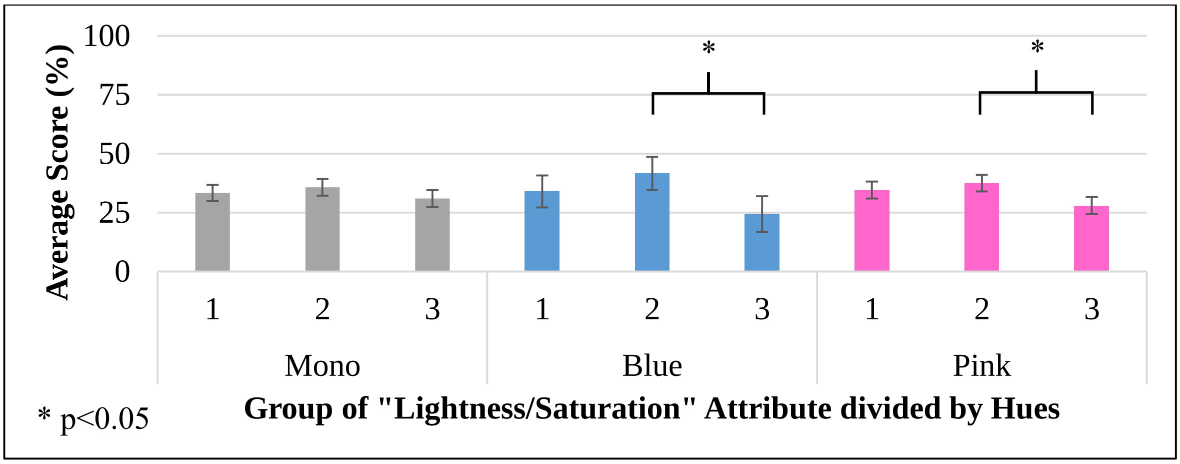



**Figure 7.14** Average scores between three levels of "lightness/saturation" attribute divided by hues

In conclusion, the experimental results showed variety of effects of each attribute for different hues of cosmetic bottle images. For "cap" attribute, flower caps were more kawaii than ribbon ones for monochrome and pink images. On the other hand, ribbon caps were more kawaii than flower ones only for blue images. For "shape" attributes, round bottle shapes were more kawaii than square ones for monochrome and pink images. Finally, for "lightness/saturation" attribute, bright colors were more kawaii than brilliant colors for blue and pink images.

#### 7.5.2.3 Questionnaire Results

I summarized the questionnaire results asking about the criteria for selecting kawaii cosmetic bottle images. The keywords that the participants usually mentioned on their answers are listed below:

- Flowers and ribbons
- Round, square shapes
- Size of cap ornamentation
- Color balance, color combination

#### 7.5.2.4 Results of Eye Tracking Data

I recalculated the average scores from the 10 participants whose eye tracking data were successfully recorded. Similar to previous experiments, I employed fixation and Area of Interest (AOI). For this experiment's analysis, I defined two AOIs for the left-side and right-side cosmetic bottle images (Figure 7.15) and created AOIs as squares with two different dimensions according to different widths and heights between round and square bottle shapes. However, the areas between the two AOIs were still equal to keep the balance of analysis areas.

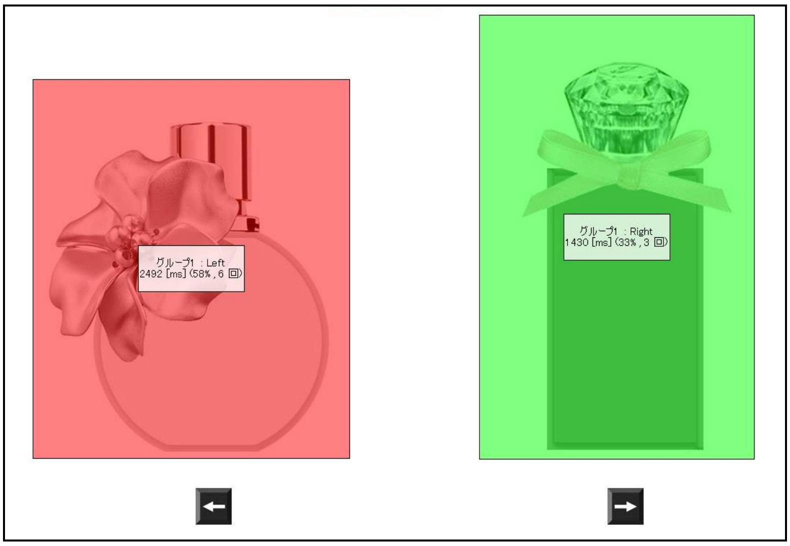


**Figure 7.15** Example of AOIs of two cosmetic bottle images with sizes corresponding to round and square shapes showing areas included in analysis of eye tracking data

I analyzed the eye tracking data by employing three eye tracking indexes from previous experiments. All of them had the same tendency as the results of previous experiments. The detailed analysis is described in the following sections.

**A. Total AOI duration**

I analyzed the total AOI durations between groups of each attribute. For each attribute of each hue, the independent-samples t-tests were run to determine the differences in average total AOI durations between the groups of that attribute.

For "cap" attribute, the results showed statistically significant differences between flower and ribbon caps for blue ($p<0.01$) and pink ($p<0.1$) cosmetic bottle images which resembled the cumulative results. There was no statistically significant difference for monochrome cosmetic bottle images. The results are shown in Figure 7.16.

For "shape" and "lightness/saturation" attributes, the results did not show any statistically significant differences between groups of any hues.

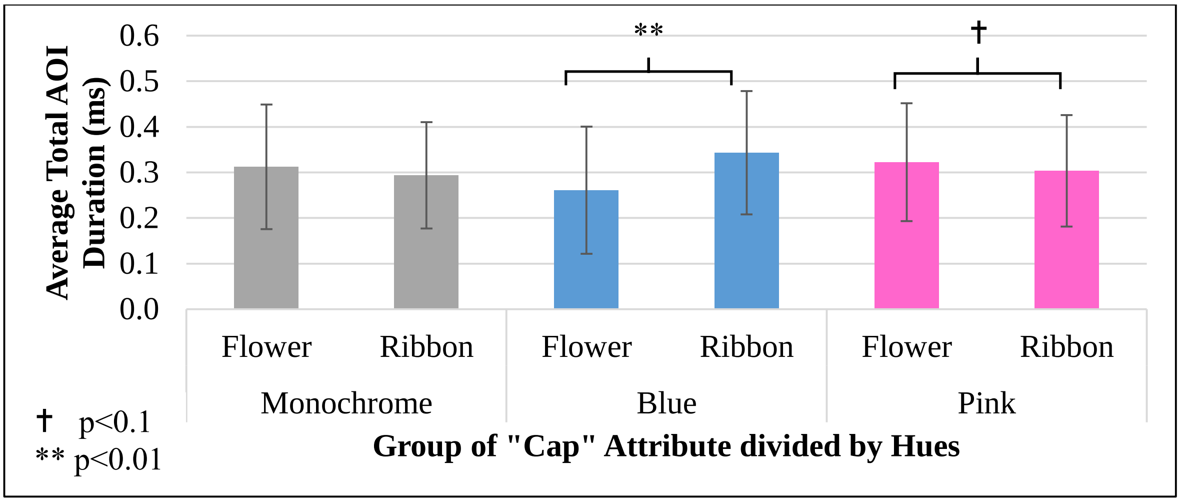



**Figure 7.16** Total AOI duration vs. group of “cap” attribute divided by hue

**B. Total number of fixations**

I analyzed the total AOI durations between groups of each attribute by using the same method of statistical analysis as that for the total AOI duration.

For “cap” attribute, the results showed statistically significant differences between flower and ribbon caps for monochrome cosmetic bottle images ($p<0.1$) which resembled the cumulative results. There was no statistically significant difference for blue and pink cosmetic bottle images. The results are shown in Figure 7.17.

For “lightness/saturation” attribute, the results showed statistically significant differences between level 1 and level 3 for blue cosmetic bottle images ($p<0.1$) which resembled the cumulative results. There was no statistically significant difference for monochrome and pink cosmetic bottle images. The results are shown in Figure 7.18.

For “shape” attribute, the results did not show any statistically significant differences between groups of any hues.

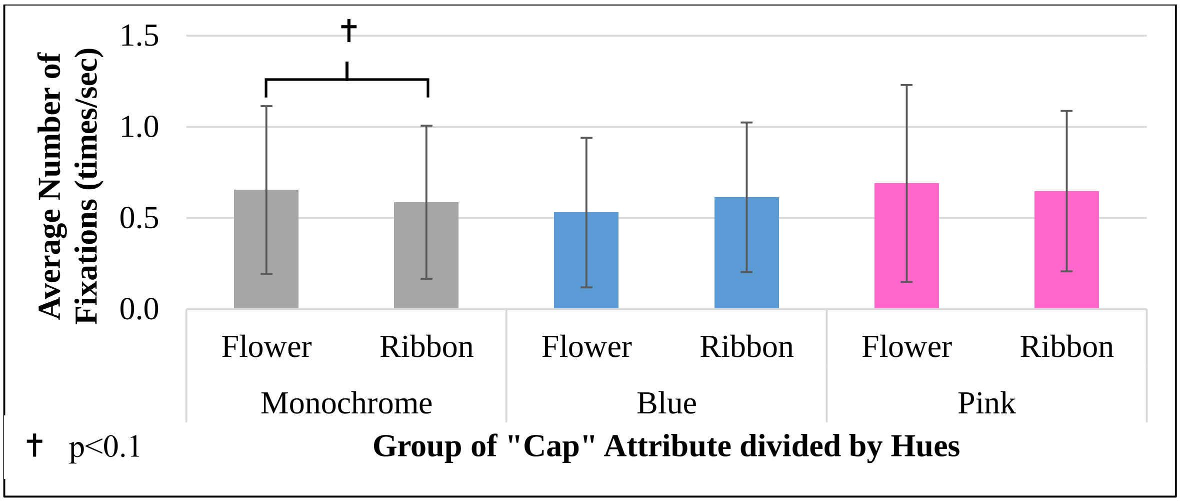



**Figure 7.17** Total number of fixations vs. group of “cap” attribute divided by hue

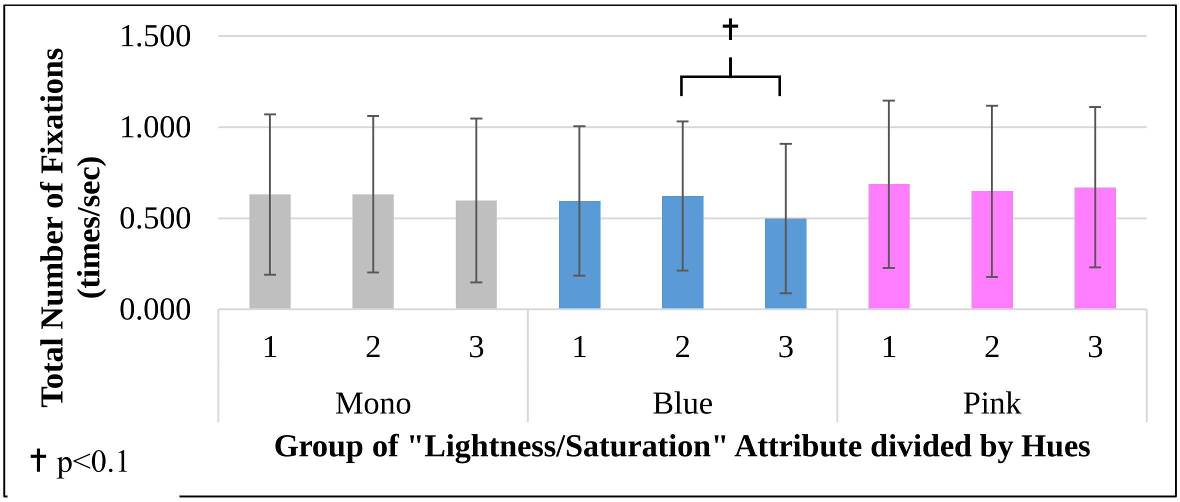



**Figure 7.18** Total number of fixations vs. group of “cap” attribute divided by hue

**C. Number of matchings between last-eye-position images and selected images**

I collected and analyzed the number of matchings for each pair of comparison between the last-eye-position image and the selected image. For each hue, independent-samples t-test was run to determine the difference in average matched and unmatched numbers. The result showed a significant difference in number of matchings between last-eye-position and the selected images ($p<0.01$) for all hues as shown in Figure 7.19.

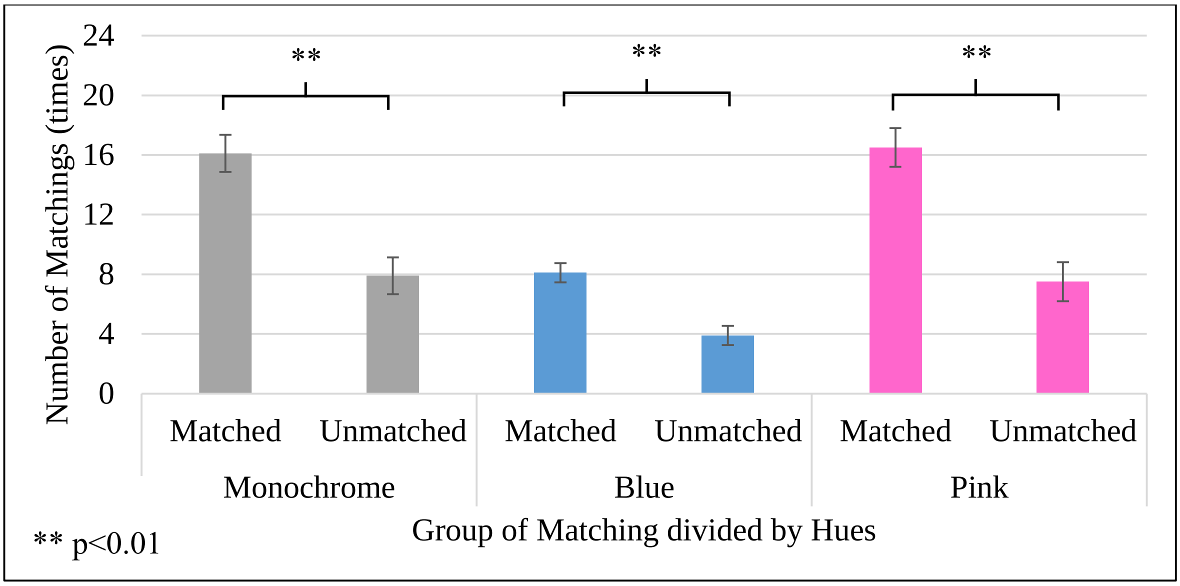



**Figure 7.19** Number of matchings between last-eye-position and selected images

From the results of three eye movement indexes described above, they showed the relationship with kawaii feelings, which was similar to the results of the previous research (Chapter 3). Therefore, I confirmed that these three indexes were useful to evaluate kawaii feelings.

### 7.5.2.5 Correlation Analysis Among Cumulative Results, Eye Movement, and Predicted Results by Model

I performed a correlation analysis among four results: cumulative results (i.e. kawaii scores), physical attributes (i.e. caps, shapes, and lightness/saturation), eye movement indexes (i.e. total AOI duration and total number of fixations), and predicted results by model (i.e. kawaii probability). To obtain the predicted results by model, I employed the constructed model in Section 7.2 to predict the kawaii probabilities of the 60 cosmetic bottle images.

I used a Pearson product-moment correlation. Pearson's correlation coefficient (r) measures the strength of association and the direction of the linear relationship between two variables. The *r* ranges from – to +1, where -1 indicates a perfect negative association, +1 indicates a perfect positive association, and 0 indicates no association. The result of correlation analysis for each hue are described below.

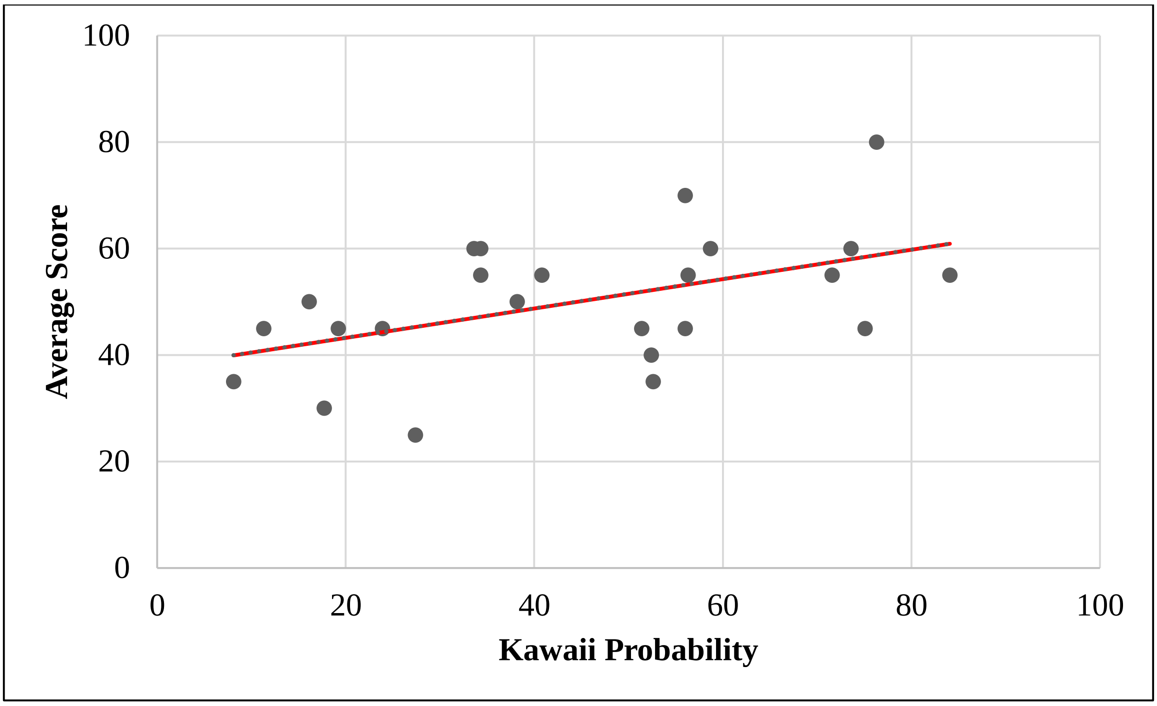



**Figure 7.20** Correlation analysis result between the average scores and kawaii probabilities of 24 monochrome images

### A. Monochrome images

For monochrome images, the result (Table 7.17) indicates the following correlations:

- Moderate correlation between kawaii scores and kawaii probability (r=.498, p<0.01) (Figure 7.20)
- Moderate correlation between kawaii scores and total AOI duration (r=.498, p<0.01).

**Table 7.17** Correlation analysis for monochrome images

| | Average Scores | Kawaii Probability | Total AOI Duration | Total Number of Fixations |
|---|---|---|---|---|
| **Average Scores** | | 0.498** | 0.498** | 0.055 |
| **Kawaii Probability** | | | 0.265 | -0.019 |
| **Total AOI Duration** | | | | 0.424* |
| **Total Number of Fixations** | | | | |

**B. Blue images**

For blue images, the result (Table 7.18) indicates the following correlations:

- Strong correlation between kawaii scores and kawaii probability ($r=.900$, $p<0.01$)
- Strong correlation between kawaii scores and total AOI duration ($r=.714$, $p<0.01$).
- Strong correlation between kawaii scores and total number of fixations ($r=.576$, $p<0.05$).
- Strong correlation between kawaii probability and total AOI duration ($r=.815$, $p<0.01$).
- Moderate correlation between kawaii probability and total number of fixations ($r=.437$, $p<0.05$)

**Table 7.18** Correlation analysis for blue images

| | **Average Scores** | **Kawaii Probability** | **Total AOI Duration** | **Total Number of Fixations** |
|---|---|---|---|---|
| **Average Scores** | | 0.900** | 0.714** | 0.576* |
| **Kawaii Probability** | | | 0.815** | 0.437† |
| **Total AOI Duration** | | | | 0.680** |
| **Total Number of Fixations** | | | | |

**C. Pink images**

For pink images, the result (Table 7.16) indicates strong correlation between kawaii scores and total AOI duration ($r=.512$, $p<0.01$).

**Table 7.19** Correlation analysis for pink images

| | **Average Scores** | **Kawaii Probability** | **Total AOI Duration** | **Total Number of Fixations** |
|---|---|---|---|---|
| **Average Scores** | | -0.208 | 0.512** | 0.251 |
| **Kawaii Probability** | | | -0.042 | 0.223 |
| **Total AOI Duration** | | | | 0.144 |
| **Total Number of Fixations** | | | | |

From the correlation analysis results, I obtained the following findings:

- For all hues, relationships between average scores and total AOI duration were confirmed, indicating the effectiveness of this index to measure kawaii feelings.
- For monochrome and blue images,
    - Average scores and kawaii probabilities had similar results. However, the tendency of pink images was not as expected, which might cause by the effects of all three attributes shown in Figure 7.14. This result indicates that the effect of pink to kawaii product is more complicated than other hues.
    - Total AOI duration and number of fixations had similar results.
- For blue images,
    - Relationship between average scores and number of fixations were confirmed, indicating effectiveness of this index to measure kawaii feelings.
    - Relationships between kawaii probabilities and the two eye movement indexes were confirmed, which ensured the effectiveness of model prediction.

### 7.5.3 Discussion

By using two eye movement indexes obtained from Chapter 3 (total AOI duration and total number of fixations), I clarified that cap ornamentation and lightness/saturation were candidates of effective attributes for kawaii cosmetic bottles.

However, this experiment used 60 modified images of cosmetic bottles, in which the caps were from original images, but the bottles were simplified causing the lack of a real sense of materials or textures. This limitation might cause the participants to focus mostly only on the cap parts. For future work, I will employ more realistic images for the evaluation.

In addition, there were some issues on eye tracking that was employed to evaluate the products as follows:

- The participants might focus on some parts of the product which might cause by not only kawaiiness but also other reasons, such as, their special design.

Therefore, it is questionable that such analysis is really correct or not. To answer this question, it is more likely that participants focus on some parts because of kawaiiness since they were asked to compare the kawaiiness of two products. Therefore, I expect that their eye movements, intensions, were forced to kawaii parts.

- Even though the eye movement indexes are the evidence to show the relationship to kawaiiness, it does not mean that product is always kawaii, but the same tendency might be obtained. Therefore, it is questionable that how I can trust the result. To answer this question, the result can be trusted because it is the result of kawaii comparison, where the participants were asked to select more kawaii images. However, these indexes might not be limited to only kawaii feelings. If I asked the participants to focus on different feeling, the same tendency might also be obtained.
- By using eye tracking, I cannot distinguish between looking at some parts or the whole image. However, I can analyze eye movement indexes to clarify that certain parts contributed to kawaii feelings more than the others by defining AOIs to those parts. For example, by using total AOI duration, I can analyze that the participants mostly fixate on caps when they are evaluating the kawaiiness of cosmetic bottles.

## 7.6 Conclusion

For the first step, I experimentally evaluated the kawaiiness of cosmetic bottle images to collect data for model construction from 15 Thai and 20 Japanese participants. From the evaluation results, only the balanced data of 8 Thai and 11 Japanese participants were used for the model construction.

Then, I continued to construct models of kawaii feelings for cosmetic bottles using the data collected from previous step. In Chapter 5, I constructed the models for spoon designs using SVM algorithm. However, the algorithm had the limitation that feature extraction was required for model construction, which was too difficult for cosmetic bottles because of their complexed attributes. Therefore, I constructed the models for cosmetic bottles using Deep CNN algorithm instead. By using this method, the limitation of SVM algorithm was solved.

Next, I employed the models to evaluate the attributes to design kawaii cosmetic bottles. The results of Thai dataset showed that the caps, especially ribbons and flowers, effectively increased the kawaiiness of cosmetic bottles. For Japanese dataset, there was only the tendency of ribbon caps to increase their kawaiiness.

Finally, I experimentally evaluated cosmetic bottle images based on their attributes using eye tracking. The relationships among average kawaii scores, two eye movement indexes, and kawaii probabilities predicted by the model were analyzed. As the results, I clarified the effectiveness of the eye movement indexes to clarify effective attributes of cosmetic bottles.

# Chapter 8

# Discussion

## 8.1 Summary of previous chapters

In Kansei engineering, it is important to design products based on customer feeling. Products that kansei values are added can make a larger impact on first impression which is a key to motivate consumer's purchase. According to success of many kawaii products, kawaii is considered as one important kansei value for future product design and development. Therefore, I conduct this research to study kawaii feelings, clarify eye movement indexes to measure kawaii feelings, constructing model of kawaii feelings, and finally clarify effective attributes to design kawaii products. I summarized my work in each previous chapter as follows:

- I described the motivation and problem statements to set my research questions and goals in Chapter 1.

- In Chapter 2, I reviewed several researches related to my thesis.
- In Chapter 3, I clarified the relationship between kawaii feelings and eye movement indexes.
- In Chapter 4, I evaluated the kawaiiness of spoon designs and indicated the limitation to apply the evaluation results to design kawaii spoons in general.
- In Chapter 5, I constructed model of kawaii feelings for spoon designs using Support Vector Machine (SVM) algorithm. I also clarified effective attributes to design kawaii spoons in general.
- In Chapter 6, I employed eye tracking to clarify the relationship between the attributes of spoon designs and eye movement indexes caused by kawaii feelings.
- In Chapter 7, I constructed model of kawaii feelings for cosmetic bottles using Deep Convolutional Neural Network (CNN) algorithm. I also evaluated the attributes to design kawaii cosmetic bottles and clarified effective ones using eye movement indexes.

This chapter discusses my research which solved all of my research questions and proved that I achieved all of my research goals.

## 8.2 Clarification of relationship between kawaii feelings and eye movement indexes

My first research question is comprised of the following parts: is there a relationship between kawaii feelings and eye movement indexes? If so, which eye movement indexes can be used to clarify their relationship? To answer this question, I set a research goal to clarify the relationship between kawaii feelings and eye movement indexes, and also proposing new eye movement indexes.

I used a comparison system and eye tracking to experimentally evaluated kawaiiness of six illustrations (Chapter 3). From the analysis of experimental results, I clarified the relationship between kawaii feelings and six eye movement indexes, in which two of them were newly identified in this research.

In summary, I confirmed that eye tracking is a new method that effectively measures kawaii feelings by using the six identified eye movement indexes. In addition, I obtained the possibility to clarify important parts of the products by using eye tracking.

## 8.3 Construction of model of kawaii feelings

My second research question is comprised of the following parts: are there any possibilities to construct model of kawaii feelings? If so, what kind of products and methods are appropriate to employ for model construction? To answer this question, I set a research goal to construct models of kawaii feelings and clarify appropriate products and methods for model construction.

To achieve the research goal, I divided the study into two steps. In the first step, I collected the evaluation results of kawaiiness of spoon designs (Chapter 4) and began to construct models of kawaii feelings for spoon designs by using SVM algorithm (Chapter 5), which confirmed that the model can be successfully constructed. Then, I continued to construct model of kawaii feelings for cosmetic bottles in the second step. However, I found the limitation that feature extraction was necessary for model construction, which cannot be performed for cosmetic bottles because they had too complexed attributes. Therefore, I collected the evaluation results of kawaiiness of cosmetic bottles (Chapter 7, Section 7.2) and used Deep CNN algorithm as a new method to construct model of kawaii feelings (Chapter 7, Section 7.3), in which the images can be used as input instead of extracted features. Finally, I suggested that Deep CNN is more effective than SVM to construct model of kawaii feelings if the products have unknown sets or complexed attributes.

In summary, I confirmed that I successfully constructed new models of kawaii feelings for spoon designs and for cosmetic bottles. In addition, I confirmed effective methods to construct model for each product, which are SVM algorithm for spoon designs, and Deep CNN algorithm for cosmetic bottles. Finally, I obtained the possibility to use the models as one useful method to evaluate kawaiiness of the products.

## 8.4 Clarification of effective attributes to design kawaii products

My second research question is comprised of the following parts: which method can be used to evaluate the candidates of effective attributes from the constructed model? Also, how to clarify effective ones to design kawaii products? To answer this question, I set a research goal to clarify effective attributes to design kawaii products using the constructed model and eye movement indexes.

From previous step of model construction, I used two algorithms to construct models. For each algorithm, the methods to obtain the candidates of effective attributes were different. SVM algorithm can generate the results of effective attributes. In contrary, Deep CNN algorithm cannot generate such results. Therefore, I developed a new method to evaluate and obtain the candidates of attributes (Chapter 7, Section 7.4), which was to modify images of cosmetic bottles and employ the constructed model to evaluate the kawaiiness of the images.

After obtaining the candidates of effective attributes, I used eye movement indexes from previous study to clarify the effective ones. From the experiment on evaluation of spoon designs (Chapter 6), I obtained the result only from one participant which can provide the suggestion for the relationship between the attributes of spoon designs and two eye movement indexes. From the experiment on evaluation of cosmetic bottles (Chapter 7, Section 7.5), I clarified the relationship between attributes of cosmetic bottles and eye movement indexes.

In summary, I confirmed that my new method to use models and eye movement indexes in combination successfully clarified the effective attributes to design kawaii cosmetic bottles. In addition, I confirmed that my method is useful both to evaluate total impression and to clarify important parts of the products.

## 8.5 Potential of this research

The novelty of this research is a new model of kawaii feelings for evaluation of product in combination with the eye movement indexes to clarify effective attributes to design kawaii products. From this thesis, I obtained the following new findings:

1. New method to construct model of kawaii feelings
2. New method to evaluate attributes using Deep CNN model
3. New eye movement indexes to clarify effective attributes

This research has some limitations as follows:

1. This research focused on spoon designs and cosmetic bottles only.
2. Only static images and paired comparison were used for eye tracking. For other kind of products such as painting and moving object, other analysis methods of eye tracking are necessary.
3. Eye tracking cannot be applied for invisible products such as voice and odor.

Even this research has some limitations, the new findings have possibilities to apply to other researches as follows:

1. Evaluation of kawaiiness for other products such as one-pieces, handbags, and stuffed animals
2. Evaluation of other kansei values such as coolness, user-friendliness, and enjoyment

# Chapter 9

# Conclusion and Future Work

In this chapter, I conclude my doctor thesis and explain future work to expand my research and recommendations for subsequent steps of this research field.

## 9.1 Conclusion

I studied kawaii feelings using eye tracking to provide effective methods measure the feelings and clarify effective attributes to design kawaii products. Below is a summary of each research goal.

To achieve my first research goal, I conducted a research that clarified the relationship between kawaii feelings and eye movement indexes. I experimentally evaluated the kawaiiness of illustrations while the eye movements were being recorded. From analyzed results, I clarified the relationship and identified two new eye movement indexes which ensured the effectiveness of eye tracking to evaluate kawaii feelings.

To achieve my second research goal, I constructed two models of kawaii feelings. First, I constructed and proposed the models for spoon designs and cosmetic bottles. For spoon designs, I performed feature extraction and then employed SVM algorithm to construct the models. However, for cosmetic bottles, the feature extraction could not be performed due to their complexed attributes. Instead, I employed Deep CNN algorithm to construct the models which did not require feature extraction. Finally, I suggested that Deep CNN is more effective than SVM to construct model of kawaii feelings if the products have unknown sets or complexed attributes.

To achieve my last research goal, I employed the results from constructed models to evaluate candidates of attributes and employed the eye movement indexes to clarify effect ones. Unlike SVM, Deep CNN algorithm cannot generate the results of attributes. Therefore, I developed a new method to evaluate the candidates of effective attributes by modifying images and using the Deep CNN model for the evaluation of their kawaiiness. Then, I employed eye movement indexes previously identify to clarify effective attributes. Finally, I made conclusion about eye movement indexes that they can be effectively used to clarify effective attributes to design kawaii products.

In conclusion, I confirmed that I achieved all of my research goals to clarify the relationship between kawaii feelings and eye movement indexes, construct models of kawaii feelings for cosmetic bottles which have complexed attributes, and clarify effective attributes using eye movement indexes. Additionally, the new findings from my thesis are also applicable to other researches focusing on other kawaii products or other kansei values that I will describe in future work.

## 9.2 Future Work

Even though my research focused only on kawaii feelings, the new findings from my thesis have possibilities to apply to other researches.

- The new eye movement indexes can be employed to evaluate various types of kawaii products (e.g. images, videos, songs) to extend their effective usage. Also, they can be employed to evaluate products targeting at other kansei values.
- The new method to construct model using Deep CNN algorithm and clarify effective attributes using the model and eye tracking are applicable for other products and other kansei values, which will be useful as evaluation tool for product manufacturers or designers.

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# Publication List

## Journal Paper

[1] **T. Laohakangvalvit**, I. Iida, S. Charoenpit, and M. Ohkura, "A Study of Kawaii Feeling using Eye Tracking," *International Journal of Affective Engineering*, vol. 16, no. 3, pp.183-189, 2017.

## International Conference Papers

[2] **T. Laohakangvalvit**, I. Iida, S. Charoenpit, and M. Ohkura, "The Study of Kawaii Feeling by Using Eye Tracking," in *International Symposium of Affective Science and Engineering (ISASE 2016)*, pp.1-7, Tokyo, Japan, 21-22 March 2016.

[3] **T. Laohakangvalvit**, I. Iida, S. Charoenpit, and M. Ohkura, "The Study of Kawaii Feeling by Using Eye Tracking," in *International Conference on Business and Industrial Research (ICBIR 2016)*, pp.283-288, Bangkok, Thailand, 12-13 May 2016.

[4] **T. Laohakangvalvit**, I. Iida, S. Charoenpit, and M. Ohkura, "The Study of Kawaii Feeling by Using Eye Tracking," in *International Conference on Applied Human Factors and Ergonomics (AHFE 2016)*, pp.185-197, Orlando, 27-31 July 2016.

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