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First Impression as a Dynamic Experience

- An Interview-Based Study of Impression Formation and Change -

제품 첫인상의 사용자 경험적 분석

: 첫인상의 형성과 변화에 관한 인터뷰 연구

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산업•조선공학부 인간공학 전공

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이 논문을 공학박사학위논문으로 제출함

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ABSTRACT

First Impression as a Dynamic Experience - An Interview-Based Study of Impression Formation and Change -

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The aim of this dissertation is to develop a conceptual framework and interview method to capture the first impression of the product as part of the dynamics of user experience. Based on a literature review on first impressions and user experience, this dissertation suggested a framework for the relationship among before-use impression, actual use, recommendation behavior, and user's underlying frame. The semi-structured interview method named the "First Impression Elicitation Method" ("FIEM") was developed here to characterize the first impression relevant to the product, which is grounded in the aforementioned framework. The major components of FIEM were the user impression

before, during, and after use, and the underlying frame of users. This method was composed of five steps: preparing, evaluating the before-use impression, evaluating the during-use impression, extracting the underlying frame, and evaluating the after-use impression.

Prior to applying this method, two exploratory studies were conducted to examine ways to solve two major issues in the analysis of interview data with the purpose of understanding the user experience. Study 1 showed the need for deriving keywords without the hierarchical categorization by comparing the results generated from hierarchical and non-hierarchical processing of the interview data. Study 2 revealed the need for deriving keywords in terms of common and distinct aspects between the major components or categories that comprise the interview.

With due consideration to the results of Study 1 and 2, Study 3 was conducted to investigate the validity of FIEM and identify the first impression of cleaners, based on the purposed method. Study 3 compared the top-ranked keywords derived from FIEM and Amazon reviews in order to demonstrate the generalization of FIEM. This study characterized the first impression relevant to the cleaners by deriving the common and distinct keywords among the before-, during-, and after-use impressions. The results provided a comprehensive consensus with previous studies on the first impressions of products, ensuring the usefulness of FIEM.

This dissertation showed several practical and academic implications. It attempted to explain the user experience components, focusing on continuous time spans, both from the macro and micro perspectives. It also provided a systemic method to researchers who are

willing to employ unstructured data for investigating user experience, from data collection to analysis. In addition to these implications, it will help designers to develop concepts that can meet to the goals of company and achieve the intended impression, by providing a basis for their decision-making. The FIEM can also serve as a research tool to gain an overall perception on a particular product, and to determine users' real desire to the products. However, despite practical implications, this dissertation was limited because it applied the proposed method to a particular type of product (i.e., a functional product). Thus, further research on diverse product types is needed to utilize the FIEM effectively.

Keywords: First impression, Dynamics of user experience, User interview, Hedonic and pragmatic values, Product design, Keyword analysis

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Chapter 1.

INTRODUCTION

This chapter presents the research background of the dissertation and defines the research problems relevant to eliciting the first impression of the product in the field of user experience design. This chapter also formulates the research questions consisting of two sub-questions in order to solve these problems. To answer these two questions, this chapter develops four objectives. At the end of this chapter, the dissertation structure is outlined.

1.1. Background and research problems

People experience various types of products in daily life, and these experiences shape their impressions of products. An impression of the product plays a central role in the user experience, and thus influences the overall evaluation of the product through the formation of subjective judgments and strong inferences about the product (Mahlke, Lemke, & Thüring, 2007; Schifferstein & Cleiren, 2005). Product impressions can lead people to have a positive or negative experience of products or services (Mizerski, 1982).

The impressions generated by products can be categorized into first, during-use, and after-use impressions, according to time span of experiences. First impressions, which are usually formed by visual interaction before actual use, play a central role in the consumer evaluations and preferences in relation to the products (Veryzer, 1999). They tend to have a strong relation to the product appearance, which can be referred to as visual appeal (Creusen & Snelders, 2002; Creusen & Schoormans, 2005). The product's visual form and color are more central to the formation of a user's first impressions.

As one of the impressions relevant to products, first impressions of products may serve as a means of conveying meaning and generating impressions related to the brand (Lindstrom, 2005; Orth & Malkewitz, 2008; Schmitt, Simonson, & Marcus, 1995). Especially, visual appeal of the products, which is related to first impressions of products, has an ability to

deliver the intended meanings to people (Henderson, Cote, Leong, & Schmitt, 2003; Rettie & Brewer, 2000). In this sense, it is important to design the first impressions of a product in order to effectively attract people, convey the products' value, and result in product selection.

Accordingly, designers should try to create first impressions that are aligned with a product concept and to can induce the intended impression of the product. To achieve this purpose, it is important to bridge the perceptual gap between users and designers (Chuang & Ma, 2001; Khalid, 2006) by gathering the users' own description of the impression of the product in order to provide meaningful insights (Demirbilek & Sener, 2003). Thus, the method for identifying first impressions of products should entail the overall understanding of the user perception and experience of a product by collecting unstructured data, such as interview data, that can explain the results from an experiment, rather than just identifying correlations between variables from structured data such as questionnaires.

However, many studies on first impressions of products have mainly focused on revealing the formation time of the first impression and the relation between first impressions and visual appeals of products (Bar, Neta, & Linz, 2006; Shalofsky, 1993; Tuch, Presslaber, StöCklin, Opwis, & Bargas-Avila, 2012). They have tended to investigate the first impressions based on questionnaires and extract several dimensions that have a powerful impact on the first impression of the product. Although these approaches can be useful for identifying the prominent factors influencing

the first impression in a structural manner, they demonstrate a limited ability to provide detailed descriptions of the factors influencing people's first impressions towards the products.

Hence, to solve these problems, it is necessary to develop a novel and systematic approach to gain a deep understanding of first impressions of products based on the collection and analysis of interview data. This method should be developed based on a comprehensive understanding of the formation process of the first impression with regard to the product. This would help product design that more effectively induces intended first impressions, which are aligned with the product's value or the brand identity, by fitting the product to expected visual experiences.

Based on these facts, the overall research question is how designers can be supported in building product concepts with regard to first impressions of products.

To address this question, three important issues need to be considered. First, temporal aspects and hedonic qualities of user experience should be discussed in the development of a method to understand first impressions of products. The temporal aspects of user experience can provide an opportunity to understand the user experience in a holistic view, from before use to after use of the product. According to the importance of these aspects, there is an increasing interest among academics in the user experience with respect to its dynamics. However, the research explaining

user experience over time is rare (Bargas-Avila & Hornbæk, 2011), because it is very time-consuming and may incur great cost.

In addition to temporal aspects of user experience, hedonic quality should be one of the main concerns in development of the proposed method for understanding first impressions of products. As aforementioned, hedonic quality is the key to creating a successful product, through providing experiences such as fun, beauty, pleasure, or enjoyment (Jordan, 2002). For this reason, researchers have been tried to evaluate hedonic dimensions of products (Bargas-Avila & Hornbæk, 2011). It may help to provide a deep understanding of hedonic qualities of the product by incorporating pragmatic dimensions with hedonic dimensions for evaluating the user experience (Bargas-Avila & Hornbæk, 2011; MacDonald & Atwood, 2013). As a user experience component, first impressions should be analyzed with regard to dynamics and hedonic qualities of experience.

Another issue is employing and analyzing unstructured data for understanding user experience. The most typical method to collect unstructured data is the interview, with the purpose of understanding participants' thoughts or feelings about the product. Although there have been considerable attempts to understand the user experience based on unstructured data, most of these studies did not provide a concrete way to analyze the unstructured data and to interpret its results (Law & van Schaik, 2010; Vermeeren et al., 2010). This may cause validation problem with using the interview data as a source of the user experience evaluation

method. Thus, it is necessary to develop a systematic way to collect and analyze the interview data, while maximizing its benefits.

On the other hand, most user experience evaluation methods have required a considerable time to collect and analysis data. Thus, due to the limited budget and time in the industrial context (MacDonald & Atwood, 2013), it is necessary to consider the development of practical methods to analyzing the unstructured data for understanding the user experience. The characteristics of practical method are summarized as lightweight, valid, applicable, and fast (Väänänen-Vainio-Mattila, Roto, & Hassenzahl, 2008). The methods need to be lightweight—that is, requiring fewer resources and skills for data collection and analysis. They also need to be fast in order to perform cost efficient and iterative evaluations. They need to be valid ensure the repeatability of the results obtained by evaluations. Finally, applicable means that the methods should take into account the various phases of product development. Depending on the product development phases, product types to be evaluated are different, such as concepts, prototypes, and products on the market. The consideration of the product development phases is an important step to establish a systematic method to evaluate the user experience (Roto, Rantavuo, & Väänänen-Vainio-Mattila, 2009).

To summarize, the practicality of collecting and analyzing the unstructured data for user experience can be characterized as dependent on the following: ease of data analysis, the reproducibility of the data collection and analysis procedure, allowing quick iteration, and the

applicability of results in terms of development phases, with a deep understanding of temporal aspects and hedonic qualities of user experience. Thus, it is necessary to develop a practical way to collect the unstructured data by providing a systematic analysis strategy. Such a strategy would help to ensure the generalizability of results while maintaining the in-depth insight possible through unstructured data. This will allow designers to enhance the user experience of the product and to gain several insights designing a new product. These facts lead to two research sub-questions: 1) how should first impression of the product be captured in terms of temporal and hedonic aspects of user experience, and 2) how should interview data be analyzed for the purpose of understanding the user experience and extracting the user's real value.

1.2. Research objectives

The main goal of the dissertation is to propose a way to identify the first impression of the product, focusing on its hedonic and temporal aspects, in order to achieve a holistic understanding of the first impression as one of user experience components. This dissertation attempts to understand the first impression of a product as the cumulative results of user's experience with various products, and refers to this characteristic as "user's experiential capital." To answer the two research questions described in Section 1.1, four research objectives are defined as follows: 1) to gain an

understanding of the characteristics of first impressions of a product in relation to consumer choice and dynamics of user experience, 2) to identify the critical issues relevant to the interview data analysis for the purpose of understanding the user experience, 3) to develop a framework and method to capture the first impression of a product with respect to temporal and hedonic aspects of user experience, and 4) to suggest suitable strategies to analyze interview data for capturing user's real desire for the product, focusing on ensuring the diversity and the representation and discrimination aspects of keywords.

In order to achieve these objectives, this dissertation pays attention to the relationship between first impressions and previous experiences with other products. This dissertation also assumes that these linkages lead to building a new experience of the product and are a key component of user's experiential capital, the accumulated information used for judging the product, in further evaluations for the first impression of a new product.

1.3. Dissertation outline

Chapter 2 reviews the previous studies relevant to first impressions, temporal characteristics of user experience, and two major issues in user experience for analyzing the interview data. This chapter explains the characteristics of first impressions in terms of use experience components,

which involve hedonic quality and the temporal aspects of user experience. This chapter also examines several challenges for interview data analysis in the field of user experience. It points out that traditional approaches are mainly based on the hierarchical categorization for analyzing the interview data, and highlights the need for a strategy for capturing both the common and hidden thoughts towards the product, through keyword analysis.

Chapter 3 presents the conceptual framework of the assumed relations among first impression, actual use, recommendation behaviour, and previous experience of the product, considering notion of user's experiential capital. This chapter also provides the overview of data collection for the proposed "first impression elicitation method" ("FIEM"). FIEM consists of four components: before-, during-, and after-use impressions, and the underlying frame. This chapter explains a detailed process to collect the information about these four components, providing concrete questions for each construct.

Chapter 4 discusses the main considerations for the analysis of interview data for the purpose of understanding user experience, based on two empirical studies. In this chapter, Section 4.1 explains Study 1, which explores the usefulness of analyzing the data in a non-hierarchical way, compared to the traditional hierarchical method. Section 4.2 explains Study 2, which suggests a way to extract the keywords focusing on their representative and discriminative aspects.

Chapter 5 provides a detailed description of Study 3, an empirical study to validate FIEM. Study 3 compares the results obtained from FIEM and user reviews in order to present the general ability of FIEM to understand the holistic user experience and the first impression relevant to the product. Based on the results of Studies 1 and 2 (see Chapter 4), Study 3 attempts to explain the characteristics of before-, during-, and after-use impressions, and the underlying frame, by means of the common and distinct keywords among those components.

Chapter 6 provides a general discussion of findings obtained from Studies 1, 2, and 3. This chapter also describes several limitations and implications of this dissertation, and discusses further research on first impressions of the product.

Chapter 2.

LITERATURE REVIEW

This chapter firstly reveals and explains the importance of first impressions of a product in terms of the time span of user experience and consumer choice. Second, the major challenges of current methods for evaluating user experience are investigated to develop an improved method for understanding the first impression of products. Finally, it identifies the characteristics of the traditional analysis methods for interview data and their limitations in two aspects: hierarchical categorization of data, and the need to focus the representation and discrimination aspects of keywords

2.1. First impression as user experience

2.1.1. First impression and consumer choice

First impressions have a significant impact on the consumers' choice of product. People tend to evaluate the overall quality of a product based on the first impression they felt immediately, while ignoring other qualities such as usability (Hartmann, Sutcliffe, & Angeli, 2008). This is referred as the "halo effect" (Nisbett & Wilson, 1977), which is caused by the confirmation bias (Mynatt, Doherty, & Tweney, 1977; Nickerson, 1998). The confirmation bias occurs when people tend to seek only information that supports their initial hypothesis, neglecting disconfirmatory evidence. Thus, a very positive first impression can extend to other qualities, and thus lead to the disregarding of later information that they will experience with the product, even its negative aspects (Campbell & Pisterman, 1996).

The most decisive factor impact on the form of first impressions is visual appeal of the product (Bloch, 1995; Creusen & Schoormans, 2005). It also has an influence on the overall evaluation of a product (Burke & Jones, 2000; Veryzer, 1999). Visual appeal is also referred to as beauty or product appearance, depending on researchers (Norman, 2005). This dissertation used the term "visual appeal," as the focus is on the impression rather than the intrinsic product character.

Visual appeal occurs immediately at first sight without direct interaction with the product (Hassenzahl, 2004; Leder, Belke, Oeberst, &

Augustin, 2004). It is formed in a very short time (Norman, 2004) and has an effect on subsequent experience (Tractinsky, Katz, & Ikar, 2000). According to Creusen and Schoormans (2005), visual appeal plays six different roles in product evaluation: 1) communication of aesthetic, 2) symbolic, 3) functional, 4) ergonomic information 5) attention drawing, and 6) categorization. This means that visual appeal, which can imply symbolic value, serves as the basis to infer the functional characteristics and the ergonomic aspects of the product (Berkowitz, 1987; Creusen & Schoormans, 2005; Norman, 1988). Visual appeal is also affected by the physical characteristics of the product, such as visual organization principles, complexity, and colors (Berlyne, 1971; Creusen & Schoormans, 2005; Whitfield & Wiltshire, 1983).

These characteristics of visual appeal imply a strong relation to the hedonic quality of the product (Hassenzahl & Monk, 2010; Tuch, Roth, HornbæK, Opwis, & Bargas-Avila, 2012; van Schaik, Hassenzahl, & Ling, 2012). According to this fact, it is important to identify the hedonic quality of the product in order to have a comprehensive understanding of first impressions. In addition to hedonic qualities, consumers also consider pragmatic quality when they choose a product to purchase (Creusen & Snelders, 2002). Understanding the pragmatic and hedonic qualities plays a critical role in developing the products that meet users' actual needs (Hassenzahl & Tractinsky, 2006; Roto, 2007). Pragmatic quality, which is instrumental and task-oriented, refers to the usefulness of a product that can help to achieve the behavioural goals while interacting with the

products (Hassenzahl, 2008). However, the increasing importance of experiential factors of the products results in an emphasis on hedonic qualities, rather than focusing on pragmatic qualities with the usability aspects (Law, Roto, Hassenzahl, Vermeeren, & Kort, 2009).

While pragmatic quality has a relation with the usability and the functionality of a product, hedonic quality focuses on its attractiveness and appeal (Hassenzahl, 2003; Mahlke & Thüring, 2007). Hedonic quality, which is non-instrumental, relates to the pleasure of use, such as a product being considered "interesting" or "fun" (Batra & Ahtola, 1991; Mano & Oliver, 1993); it aims to fulfill be-goals beyond the efficiency of the product and has three main aspects (Hassenzahl, 2003): stimulation (novelty, change, personal growth, development of knowledge and skills), identification (self-expression and communication of own identity to others, relatedness), and evocation (provoking memories, symbolizing). Hedonic quality also has a more positive and stronger relation to need fulfillment and optimal satisfaction in user experience, compared to pragmatic quality (Hassenzahl, Diefenbach, & Göritz, 2010; Partala & Kallinen, 2012). Thus, the core of hedonic quality is appeal and enjoyment. For this reason, people place great importance on hedonic aspects of the product.

Although people more prefer hedonic products, they tend to choose pragmatic products instead of hedonic products (Chitturi, Raghunathan, & Mahajan, 2007; Khan, Dhar, & Wertenbroch, 2005; Okada, 2005). This phenomenon is called the hedonic dilemma, which refers to a gap between choice and experience that can be explained by the tendency to justify

pragmatic attributes more easily than hedonic attributes (Diefenbach & Hassenzahl, 2011; Okada, 2005). For example, even if people are enthusiastic about the first impression of the product, they may not purchase the product due to a lack of justifiability for their choice.

This dilemma can be reduced by enhancing the justifiability of hedonic choice and by manipulating the need for justification by framing the choice context (Diefenbach & Hassenzahl, 2011). These solutions may help consumers to become immersed in the first impression of the product, and thus to make the purchase. For example, we may maximize the first impression by displaying a product with an additional explanation of hedonic values for the product or by emphasizing its hedonic quality, in the context of showrooms or online and offline stores.

Considering the abovementioned facts, first impressions should be understood based on their influences on subsequent experience with the product and the characteristics of consumer choice and hedonic qualities, which have a strong link to visual appeal. Another characteristic of the hedonic quality is that the relative dominance of the hedonic and pragmatic qualities can change over time, in terms of the time span of user experience (Karapanos, 2013; Kujala, Roto, Väänänen-Vainio-Mattila, Karapanos, & Sinnelä, 2011; von Wilamowitz-Moellendorff, Hassenzahl, & Platz, 2006). Hence, the consideration of temporal aspects of user experience is needed to properly understand and evaluate first impressions of the product.

2.1.2. First impressions and dynamics of user experience

User experience can be defined as dynamic, context-dependent, and subjective characteristics (Hassenzahl & Tractinsky, 2006). Due to its temporal aspects, user experience changes over time (Karapanos, 2013) and shows different aspects in terms of the time span, such as before, during, after, and overtime periods of usage (Allam & Dahlan, 2008; Roto, Law, Vermeeren, & Hoonhout, 2011).

According to Roto et al. (2011), before-use of the product, anticipations, or expectation play an important role in the evaluation of the product. Anticipations have a relation to prior exposure to the product, such as previous experience, information from other sources, and intention of use (Law et al., 2009; Roto et al., 2011). It has influence on shaping subsequent experience. Anticipated user experience can be associated with during usage, after usage, over time usage, as well as before first use, because it mainly relies on the imagination of use of the product, instead of interacting with the product (Roto et al., 2011). This characteristic of anticipated user experience results in a lack of evaluation method in the early stage of product development, because of the difficulty of imagination (Vermeeren et al., 2010).

During usage of the product, people can interact with the real product, which comprises momentary user experience. This can be seen as the core of user experience, because the actual use helps to capture the dynamic internal state of users and the context of use, based on the direct

interaction in a real time. After usage of the product, people have an episodic experience for a specific period of time. According to the continuity of user experience (Kujala, Minge, Pohlmeyer, & Vogel, 2012), it is necessary to understand "overtime" usage of the product, which refers to a cumulative user experience ranging from before use to after use. It can help to evaluate the product holistically. The duration of cumulative user experience can vary.

Several researchers have been interested in this experience and have attempted to develop a method to understand such long-term user experience of the product, such as the experience sampling method (ESM), the day reconstruction method (DRM), and the UX curve. ESM (Hektner, Schmidt, & Csikszentmihalyi, 2007) aims to collect the information about people's feelings and thoughts by self-reports during specific moments of their daily lives in real time. DRM (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004) is a self-report method that asks people to reconstruct their daily lives before sleep and to pick the most meaningful experiences. This method may reduce the burden on participants and minimize recall bias, compared to ESM. UX curve (Kujala et al., 2011) aims to help participants to remember how and why their experience with the product has changed over time in a retrospective manner. Unlike ESM or DRM, it tries to understand a long-term product use as a trend, not a simple sum of the individual experiences.

Designers should consider aforementioned temporal aspects of user experience (Karapanos, Zimmerman, Forlizzi, & Martens, 2010; Kujala et al.,

2011) to create a successful first impression. First impressions, as a construct of user experience, involve several characteristics to consider in the evaluation. First, they occur before usage phase, and thus should be evaluated without any direct interaction with a product during a very short time (Bar et al., 2006; Lindgaard, Fernandes, Dudek, & Brown, 2006).

Second, first impressions can be related to anticipated user experience or cumulative user experience because of the relationship between anticipations and subsequent experience of the product. The phases of experience have no fixed sequences and they may overlap (Roto et al., 2011). This fact implies a need to evaluate the first impression based on cumulative time span, which has a relatively short duration compared to a long-term usage. As mentioned above, anticipations are affected by previous experience (Law et al., 2009); thus, understanding the previous experience might help to provide a holistic view to evaluate the first impression of a product.

Third, the first impression also has a momentary user experience aspect. Despite lack of any direct interaction with the product, people build a first impression of a product by seeing, not by imaging it. As a momentary user experience, first impressions may have a linkage to actual use of the product. This indicates that first impressions can provide an inference of functional qualities of the product (Berkowitz, 1987; Norman, 1988).

Finally, first impressions can be associated with the recommendation behaviour in terms of a long-term experience. According to Kujala et al. (2011), attractiveness, as hedonic quality, showed explanatory power on the changes of user experience as well as a significant relation to satisfaction and willingness to recommend the product to other. This can be explained by the peak-end rule, that means people tend to judge an experience based on its peaks and ends, rather than based on the average perception of the experience (Hsee & Hastie, 2006; Kahneman, Fredrickson, Schreiber, & Redelmeier, 1993). If people remember the first impression as the peak of experience, the overall experience will be determined by the first impression, similar to the halo effect mentioned above (Nisbett & Wilson, 1977). Thus, it is needed to consider the recommendation behaviour for the evaluation of first impressions of a product.

These facts indicate that first impressions of products are derived from ever-changing experience. Hence, the first impression of the product can be explained by its relation with anticipations, actual use, previous experience, and recommendation, also considering temporal aspects of user experience.

2.2. Challenges for interview data analysis on user experience

Previous studies on user experience have focused mainly on structured data obtained from a questionnaire in order to evaluate the user experience of the product. Structured data refers to information that is originally expressed numerically. Although these approaches are useful for modeling and identifying a relationship between affective or usability factors, they have been shown to lack detailed description of the factors influencing people's judgment on a specific product.

The impression of a product can be affected by the individual or the social prejudice, preference, or memory (Demirbilek & Sener, 2003). As Augoyard and Torgue (2014) claimed, people usually perceive products through subjective interpretation, shaping the impression of products based on contextual factors such as attitude, psychology, or their culture. However, questionnaires consisting of predefined measures are not suitable for capturing the contextual or cultural factors such as user's attitude, belief, custom, or prejudice regarding the product. Besides, structured data is obtained by predefined measures; thus, the information which is not included these measures is disregarded. The general strategy for analyzing structured data is to reduce the data to several factors. These facts may lead to missing the insights that are valuable to understand user experience related to the product and prevent acquisition of diverse information about the user experience (Swallow, Blythe, & Wright, 2005).

To overcome these limitations, unstructured data, such as interview data, gains an increasing importance in the field of user experience, compared to structured data, such as questionnaire data (Bargas-Avila & Hornbæk, 2011; Law & van Schaik, 2010; Vermeeren et al., 2010). Compared to structured data, unstructured data can provide detailed and rich information for user experience (Swallow et al., 2005), and thus can help to elucidate the hidden needs or actual desires of people.

However, most user-experience research utilizing unstructured data is reported without describing the data collection process or data analysis method in detail (Bargas-Avila & Hornbæk, 2011). Moreover, most of them just resulted in new dimensions, which can only explain the characteristics of generic user experience and have no clear link to pre-established dimensions of user experience. It is also difficult to guarantee the generality and the statistical significance of the results of unstructured data (Law & van Schaik, 2010), compared to the results of structured data. These facts may cause a validation problem with using the unstructured data for user-experience analysis. This is due to the difficulties in collecting and analyzing of unstructured data, as well as data interpretation problems (Vermeeren et al., 2010), weakening reliability of unstructured data as a basis for understanding the user experience. Thus, it is necessary to develop a practical way to analyze the unstructured data that can help to ensure generality and to extract the essence of the results, in order to enhance the user experience of products and to provide several insights for design of new products.

Thus, analyzing unstructured text data to understand the user experience is challenging for the following reasons: 1) hierarchical categorization and data richness and 2) representation and discrimination aspects of keywords.

2.2.1. Hierarchical categorization and data richness

The interview is the most popular way to collect unstructured data in the field of user experience. There are various methods to analyze the interview in order to identify user experience or use value of product, such as content analysis (Krippendorff, 2012) and laddering technique (Abeele & Zaman, 2009; Reynolds & Gutman, 1988), discussed in turn below. These methods are typically based on an inductive approach, which aims to identify the patterns, themes, and categories that are directly drawn from the data (Patton, 1990). Based on the inductive approach, grounded theory provides the basic framework for understanding a phenomenon by deconstructing it as categories, themes, concepts, and constructs, and thus for generating theory through open, axial, and selective coding (Corbin & Strauss, 1990; Glaser & Strauss, 2009).

Content analysis is the typical traditional technique to analyze interview text by compressing the data into categories and by organizing it in a hierarchical way such as main themes, sub-themes, and sub-sub-themes (Kassarjian, 1977; Krippendorff, 2012). Content analysis can be

carried out based on inductive or deductive categorizations. As mentioned above, the inductive approach generates categories directly from the text, whereas the deductive approach analyzes the text using predefined categories derived from a literature review (Cavanagh, 1997; Cho & Lee, 2014; Mayring, 2002). The content analysis consists of selecting the unit of analysis, creating categories, and finding themes by linking categories.

Similar to content analysis, laddering is an analysis technique used to understand how consumers translate the attributes of products into meaningful associations based on the Means-End Chain theory (Reynolds & Gutman, 1988). The main concept of laddering is to connect product attributes (A: Attributes) sequentially to consequences of product use (C: Consequences) and individuals' values (V: Values) according to the levels of abstraction (Veludo-de-Oliveira, Ikeda, & Campomar, 2006b). The data analysis of laddering consists of identifying categories, classifying categories into A, C, V codes, and discovering the A-C-V links.

Although these methods can manage a large amount of data and to draw the logical flow in data, they have crucial limitations because of their hierarchical processing method, which classifies content into the levels of abstraction in addition to grouping similar content.

First, the hierarchical processing approach may inhibit opportunities for interesting insights or thoughts from interview data, which may defy classification as hierarchical components (Lin, 2002; Veludo-de-Oliveira, Ikeda, & Campomar, 2006a). In content analysis, each

unit from the text should belong to a category among mutually exclusive categories (Cavanagh, 1997). Themes are established by linking relevant categories; thus, they have a hierarchical linkage with categories. This hierarchical structure can be shown in the laddering technique. All categories are classified as attributes, consequences, or values, and then used to create hierarchical ladders that form A-C-V links. Second, while performing content analysis, researchers have to select and categorize variables according to their subjective opinions. This task may allow the elimination and simplification of relevant variables (Lin, 2002). Finally, the process of generating the hierarchical structure requires a considerable amount of time from the researcher, which invokes higher costs and a greater complexity in analysis (Botschen, Thelen, & Pieters, 1999; Kondracki, Wellman, & Amundson, 2002).

In addition to these limitations, according to Phillips and Reynolds (2009), the previous studies on CPV using the laddering approach did not offer clear evidence that a consumer's actual value structure forms a hierarchy. Whitlark and Allred (2003) noted that, laddering showed the logical flow of information rather than representing the natural flow of thought. Furthermore, understanding consumer values or needs should be based on interdisciplinary and qualitative approaches, because the values are by nature very complex and subtle concepts (Gallarza, Gil-Saura, & Holbrook, 2011). These facts and aforementioned shortcomings encourage the need for a new approach to elicit consumer values or needs relevant to user experience in a non-hierarchical way.

2.2.2. Representation and discrimination aspects of keywords

With the advent of text mining techniques, text can be more easily summarized by means of keywords from the text, compared to using the traditional content analysis. Similar to content analysis, this enables researchers to understand the characteristics of a particular text based on keywords or phrases (Lin, Hsieh, & Chuang, 2009). In this sense, it can be considered as an advanced form of content analysis that is based on exploratory data analysis (Hearst, 1999). However, there have been few attempts to analyze the interview data by using text-mining techniques.

Regardless of the type of analytical method, the main concern of unstructured text data analysis is to extract proper and meaningful keywords that can effectively represent the interview text. When considering keywords as the units of analysis, two critical questions can be emerged: What are descriptive keywords for a text? And, how can both common and hidden needs be identified from the results derived by keyword analysis?

Many studies on keyword analysis define keywords based on raw word counts or term frequency – inverse document frequency (tf-idf) scores (Salton & Buckley, 1988). Raw word counts simply show the frequency of words by rank. The tf-idf score is the most popular frequency statistics used for information retrieval. This technique helps to identify words with both a high frequency within a document and a low frequency among all documents (Joachims, 1997; Salton, 1991). Although they can help to

provide a basis to determine the keywords, using raw counts or tf-idf alone may show a limited ability to summarize the text (Chuang, Manning, & Heer, 2012). In this sense, it is necessary to understand the text from multiple perspectives.

Kageura and Umino (1996) suggested several ways to define the keywords with the ability to index the text, in terms of the representation and discrimination aspects of keywords. The keywords with the ability to represent a document can be identified as follows: 1) a word that appears in a document is likely to be an index term, and 2) a word that appears frequently in a document is likely to be an index term. The keywords with the ability to discriminate documents can be identified as follows: 3) a word that appears only in a limited number of documents is likely to be an index term for those documents, and 4) a word which that relatively more frequently in a given document than in the whole database is likely to be an index term for that document. Based on this approach, the keyword analysis method based on raw word counts has similar characteristics to the former perspective (1 & 2), whereas tf-idf can be considered similar to the later perspective (3 & 4), which more emphasizes the discrimination aspects of keywords.

These two perspectives may help to analyze the interview data for the purpose of understanding the user experience for the product. Keyword analysis in user experience research should aim to identify user's feelings, thoughts, attitudes, or values towards the product, and thus to provide an opportunity to extract not only general perceptions or

impressions of the products, which refer to common needs, but also hidden needs. The hidden needs can be interpreted as unique factors with the ability to distinguish between products or between impressions that users have in their minds. Hence, it is necessary to develop a keyword analysis strategy that can uncover both general and unique aspects of user's thoughts about the impression of products, from the representation and discrimination aspects of keywords, in order to have a deep understanding of the user experience using interview data.

2.3. Summary

First impressions, representing hedonic quality of the product, play the key role in consumer choice. People tend to prefer products with good first impressions, but they need justification to proceed to a purchase based on the first impression of the product. This is because they tend to evaluate the product with pragmatic qualities, which are related to the functional aspects of the product. In terms of temporal aspects of user experience, the first impression is generated before use, but it is also related to the feelings evoked during and after use in the consideration of long-term user experience. Due to the complexity and continuity of the first impressions, analysis based on the unstructured data and the temporal aspects of user experience is necessary for a better understanding of first impressions. Thus, the first impression of a particular product should be identified in the

relationship with actual use of the product and the recommendation behaviour, using unstructured data. However, to use the unstructured data for a deep understanding of user experience, researchers should consider two issues discussed above related to analyzing unstructured text data: 1) hierarchical categorization and data richness and 2) representation and discrimination aspects of keywords. In this sense, it is necessary to analyze the text from interviews with consideration of the representation and discrimination aspects of keywords, using a non-hierarchical processing method.

Chapter 3.
DATA COLLECTION OF THE FIRST IMPRESSION ELICITATION METHOD (FIEM)

The dissertation aims to provide an interview method to understand the first impressions of products in terms of user's experiential capital, which involves the experience of actual use, recommendation, and the underlying frame, as well as the first impression. To this end, this chapter will describe the conceptual framework for identifying the first impression in terms of user's experiential capital as well as defining user's experiential capital and its components. This chapter will also explain the details of collecting the interview data in five steps: 1) selecting the products used in the interview and recruiting participants, 2) capturing users' first impressions of those products in a short time before use, 3) collecting users' opinions and feelings during use of those products, 4) extracting the values and thoughts that users have in mind for the products before the interview, and 5) investigating users' further expectations towards the products after use.

3.1. Conceptual framework

As pointed out Section 2.1, the first impression of the product should be understood with consideration of usability issues and the recommendation behaviours, as well as the temporal aspects of user experience. People tend to establish the first impression of a product not only by their immediate judgments but also by their prior experience with the products. In this perspective, the first impression of the product can be defined as an immediate judgment based on the user's cumulative experience of the products.

This dissertation addresses the cumulative aspect of the first impression of the product, with a focus on the temporal aspects and hedonic quality of user experience. As described in Section 2.1.2, people usually experience a product through before, during, and after usage. This overall process comprises experiential capital, which can refer to the results of feelings, thoughts, or values generated by the indirect and direct interactions with the product.

Before using the product, people experience the first impression of the product. In the during-use phase, their experience focuses on the functionality aspects of the product. After using the product, they generate their reviews on the advantages and disadvantages of the product and think about whether they recommend the product to others or not. These experiences will serve as an underlying frame, which is the collection of their previous experiences, when people will experience a new product.

Through this iterative process, people can accumulate experiential capital. In this sense, people may evaluate the first impression of the product through the active interaction with their experiential capital and their instant judgments on the product. Figure 3.1 describes the conceptual framework of the first impression elicitation method (FIEM) and the notion of a user's experiential capital.

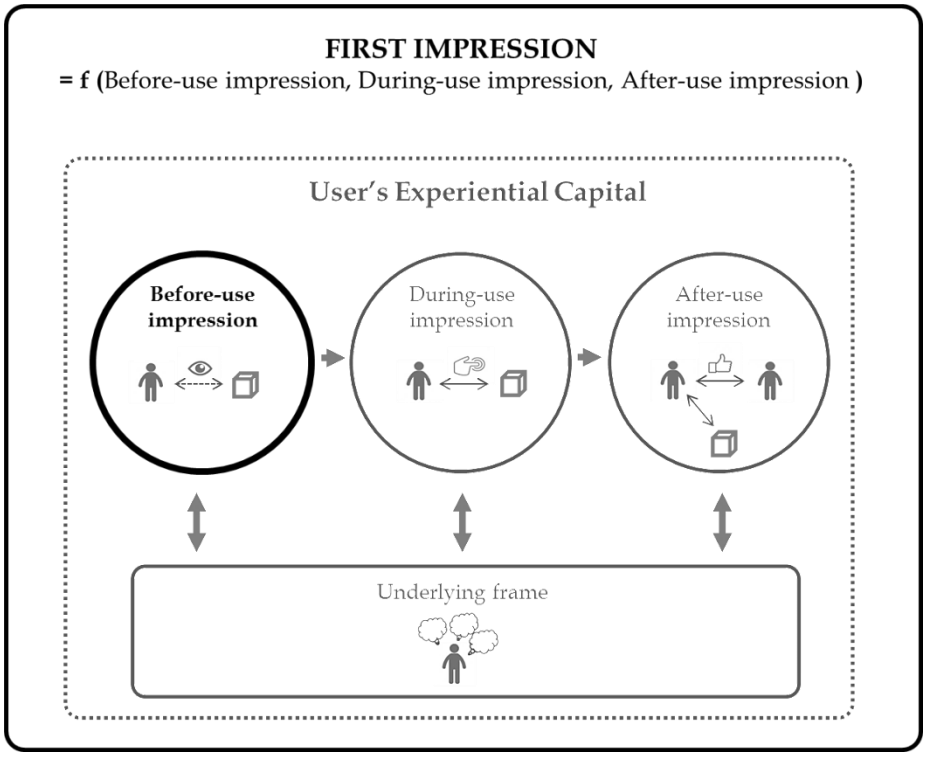


Figure 3.1 The conceptual framework of FIEM

To sum up, the conceptual framework of FIEM focuses on the data collection from before and during use, recommendation behaviour after usage, and the underlying frame, as the user's experiential capital.

3.2. Method of data collection: Semi-structured interview

FIEM is designed to capture the temporal impressions of the product with a semi-structured interview. The semi-structured interview refers to an interview with a list of key themes, issues, and questions to be covered, but where the interviewee is allowed the latitude to diverge from those topics (Kajornboon, 2005). As shown in Figure 3.1, the key components of FIEM consist of the impressions of before, during, and after use, and the underlying frame of users. A more detailed summary of the interview questions is listed in Table 3.1.

The data collection for FIEM is performed in five steps: 1) preparing the interview, 2) evaluating the before-use impression, 3) evaluating the during-use impression, 4) extracting the underlying frame, and 5) evaluating the after-use impression.

Table 3.1 Components of FIEM

Components	Descriptions
Before-use impression	What were your feelings or thoughts when you first saw this product in the consideration of product appearance?
During-use impression	What did you think while using the product?
Underlying frame	What are the advantages and disadvantages of your product you currently have?
	What is the role and meaning of the product you have in mind?
	What are your memorable anecdotes related to the product?
After-use impression	What is your ideal type of this product?
	What will you consider when you give this product to your friends as a gift?

3.2.1. Preparation and initiation

Before the interview, the researcher should select the products to be utilized in the interview and recruit the participants. There should be more than two types of products, because this can provide a point of reference to participants, and thus enable them to represent their feeling and thoughts more easily. In addition, products on the market are evaluated in relative terms, not in absolute terms. However, the large number of products can increase the burden of evaluation for participants and the duration of

interview. Thus, products to be used in interviews should be selected carefully with consideration of quality of data and interview time.

3.2.2. Evaluating the before-use impression

As mentioned in Section 2.1.1, the first impression of products has a strong relation with product appearance and feelings that are formed in a short time. Based on the characteristics of first impression, the aim of this step is to collect the first image of the product in the context of "before use" and without direct interaction, while focusing on product appearance. One of the characteristics of the first impression is that it is usually formed in a short time. Thus, this aspect should be considered in the design of the interview.

In this step, when participants come to the laboratory, researchers provide a brief description of the product to participants, and then they should look around the products to be used in interviews for five minutes, without interacting with it physically. At this time, researchers ask to participants to imagine the context of buying these products in the store. After this activity, researchers perform an in-depth interview with participants based on the questions described in Table 3.1.

The important points of this step are to evaluate a given product 1) imagining the context of buying a product in the store, 2) allowing a five-

minute for "shopping," and 3) while quickly browsing products. This dissertation will refer to this approach as the five-minute snapshot.

3.2.3. Evaluating the during-use impression

During-use experience of the product means the experience which induced by direct interaction with products. In this step, researchers collect users' immediate thoughts that occur during the use of the product while performing simple tasks. Participants are asked to select and use the product according to their previously assigned first impressions rankings. According to the think aloud method (Lewis, 1982), they are required to say whatever comes into their mind while performing the simple task, interacting with the product, including positive and negative aspects of the product usage. This approach provides an opportunity to capture the impression of the product during use, avoiding the distortion through reconstructing memories in a later interview.

3.2.4. Extracting the underlying frame

"Underlying frame" refers to the value that users have in mind for the product before beginning the interview, such as meanings, roles, or episodes related to the product. Identifying the underlying frame is

important to capture a user's initial thoughts or attitudes towards the product, which act as a reference to evaluate the newly exposed products.

In this step, participants are asked to describe any brief episodes in relation to the products, their perceived meaning and role of the products, and the advantages and disadvantages of the product currently being used by their household. This information will help to provide an explanation on the first impression evaluation of the product. In this regard, this step includes three questions as described in Table 3.1.

3.2.5. Evaluating the after-use impression

After the use of the product, FIEM collects users' thoughts and further expectation in terms of two aspects: what the ideal type of product is and which elements should be considered as a gift for friends. These aspects are a reflection of users' recommendation behaviours. Recommendation is an outcome generated by an actual use of the product. Thus, in FIEM, users' expectation of the improvement of the product and the perceived most important characteristics of the product as a gift serve as a proxy for recommendation.

This step employs sketching along with in-depth interview to improve the ability of the participants to represent their thoughts or feelings. Sketching, as a means of extracting more creative ideas and

supporting idea generation, can help to support lateral thinking (De Bono, 2010), which refers to creative and indirect ways to solve a problem, and short-and long-term memory in terms of enhancing creativity and richness of ideas (Craft & Cairns, 2009). Therefore, it reduces the cognitive load of generating ideas and can be used as a valuable thinking tool as a way of external representation (Fallman, 2003; Schön, 1983; Suwa & Tversky, 2002).

During this step, participants are required to point out components of the product to improve with a brief illustration of the product composed of lines without colors. They should provide a description of how to improve the products with a simple sketch of their ideas, as well as indicate the parts to be improved in the picture. After completing this activity, participants are asked to explain their ideas and thoughts to researchers. They are also required to describe the main points to be considered as a gift to their friends. Thus, this step includes the two questions as described in Table 3.1.

3.3. Summary

Data collection of FIEM consists of five main steps: preparing, evaluating the before-use impression, evaluating the during-use impression, extracting the underlying frame, and evaluating the after-use impression. Interview participants are asked to browse given products in five minutes for

capturing the before-use impression (i.e., the five-minute snapshot). In the next step, they freely express their thoughts in words during the use of given products according to the think-aloud technique. User value related to given products, which can refer to underlying frame, is also explored. Finally, users' thoughts related to their recommendation behaviours are revealed by using a sketching technique. Data explaining the four components of FIEM can be collected through these steps. To identify the key information of each component, the main considerations for interview data analysis will be discussed in the next chapter.

Chapter 4.

INTERVIEW DATA ANALYSIS

This chapter aims to examine the main considerations for the analysis of interview data with the purpose of capturing the user experience of the product. As mentioned in Section 2.2, traditional analytical approaches to interview data have two major limitations. One is data loss resulting from hierarchical classification of interview data, such as assigning a predetermined label. The other problem is the lack of an effective and easy approach for deriving the representative keywords from the interview, in a systemic way. These problems should be considered prior to the analysis of the interview data. In this sense, this chapter demonstrates two empirical studies that can solve the abovementioned problems. Study 1 showed the need for deriving keywords without the hierarchical categorization by comparing the results generated from hierarchical and non-hierarchical data processing. Study 2 suggested the need for deriving keywords in terms of common and distinct aspects between the major components that comprise the interview.

4.1. Deriving keywords without hierarchical categorization

This section aims to reveal the need to process the interview data in a non-hierarchical manner in order to prevent data loss generated by traditional data analysis approaches and to increase the richness of data. To suggest a way to overcome several limitations described in Section 2.2.1, the comparison of hierarchical and non-hierarchical processing results was performed in the context of identifying the value structures of users generated by semi-structured and in-depth interviews. In Study 1, semantic network analysis was employed as a tool to extract the keywords from interviews. It can be considered as an advanced form of content analysis that is based on text mining and mainly used in consumer research for the purpose of analyzing the unstructured data from quantitative perspectives in a systematic way (Kassarjian, 1977; Krippendorff, 2012).

Semantic network represents an abstract description of the relationships between concepts or words derived from the data (Quinlan, 1968; Spitzer, 2000). The semantic network consists of nodes, which represent concepts, and links describing the association between these concepts (Brachman, 1977). Its basic idea is grounded in the network structure of memory as a set of associations among concepts (Anderson, 1983). This characteristic of semantic network analysis may help to uncover the knowledge structures that users have in mind.

4.1.1. Method

As shown in Figure 4.1, the overall process of this study consists of three phases: 1) collecting interview data, 2) transforming raw data into structured data, and 3) visualizing and analyzing the network.

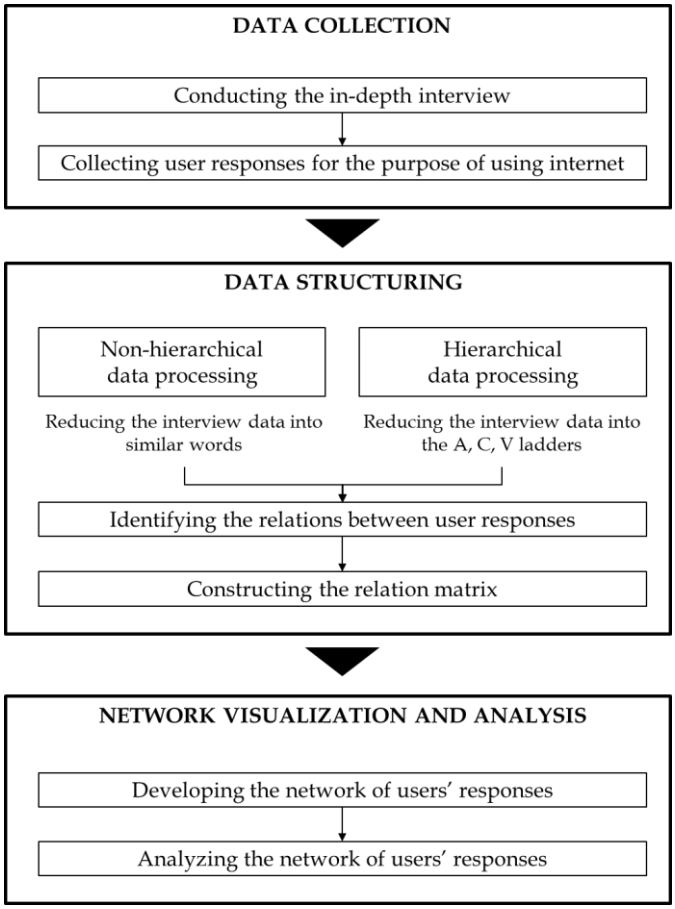


Figure 4.1 The overall process of Study 1

In the data structuring phase, data are processed both with hierarchical and non-hierarchical ways. In this study, nodes in the network indicate words derived from the interview and its connection is represented by links. The difference between two approaches is that whether the steps for classifying words into the levels of abstraction are included or not. Compared to hierarchical analysis, the non-hierarchical processing approach only requires a step for grouping similar words together. For the empirical research, case study was conducted on the value structure of the Internet usage behaviour of teenage users.

Data collection

Semi-structured and in-depth interviews were performed with 17 participants (8 males and 9 females), whose ages were between 16 and 19. These participants were recruited according to their interests in the use of Internet: game (7 participants: 4 males and 3 females), fashion (5 participants: 2 males and 3 females), and celebrity (5 participants: 2 males and 3 females).

The interview is composed of two phases: 1) what is the type of information they want to search in the Internet, and 2) why this information important to them. First, each participant was asked to describe the type of information they were searching in the Internet. In the next phase, participants were required to provide the reason for searching

the abovementioned information and why it is important to them. During the interview, researchers repeatedly asked to participants the reason of their responses according to the laddering interview technique (Reynolds & Gutman, 1988). All responses of the participants were recorded.

Data structuring

To construct a network, it is needed to convert unstructured data from interviews into structured one. The data structuring involves reducing the interview data into similar words and into attributes, consequences, and values, identifying the relation between words, and generating the relation matrix. The first step of data structuring is to divide sentences from interviews into meaningful units according to propositional theory. Propositional theory helps to extract the "fact" and "context" elements from a sentence as a means to systematically condense the data (Anderson & Bower, 1974). The fact element can refer to user's behaviour, judgment, or feeling on a given product. The context element has a relation with phrases including places or time.

The second step is to identify the similarities among words and to remove data redundancy by grouping words with similar meanings. During the non-hierarchical analysis, each sentence from interviews was divided into words, and then these words were grouped according to their similarities. To ease of analysis, it is needed to perform a task to assign

numbers to each group of similar words. In addition to integrating the relevant words, the hierarchical data analysis required classifying and labeling each word with the attributes, consequences, and values. In this study, the hierarchical method resulted in 30 attributes, 33 consequences, and 8 values (Appendix A).

The final step is to calculate the relation frequency between each word, and thus to generate the relation matrix. The interaction between two words is defined when the "word 1" is the description of "word 2" or is the cause of "word 2". In the interview, we repeatedly asked participants the reason of preference for a given service. This interview process provided the repeated linkage between reasons of preference, thus we defined the interaction between two words as a form that A is the cause of B. For example, if the participant "this product is beautiful because it gives me confidence," there is an interaction between "beauty" and "confidence".

Based on these assumptions, the results of data structuring were recorded in a relation matrix by calculating the frequency of interaction between words. The words in each row and column indicated the given node and received node, respectively. The cells within the matrix contain a figure that corresponds to the number of times that a word in the row connects to the column word. Example of data structuring was attached in Appendix B.

Semantic network visualization and centrality analysis

Semantic network analysis was employed as a tool to analyze and represent the data obtained from both hierarchical and non-hierarchical processing methods. It helped to understand the data based on the connections between words in the data, regardless of the processing techniques. In the semantic network, nodes represent words extracted from the interviews and links represent the connection between words.

The importance of nodes, which represent words, can be derived by using the centrality measures in network analysis. Centrality measures can help to identify the influence and powerfulness of nodes in the network (Scott, 2000). Therefore, words with a high centrality can be considered as the key value. The most popular centrality measures are as follows: degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality.

Degree centrality helps to identify a word with just a large number of direct links to other words. This means that a particular word has a lot of simple connections to other words can be considered as the key consumer value based on degree centrality. Degree centrality defines the importance of a node as the number of link incidents on a node, focusing on capturing the major channel of information within the network (Freeman, 1979). The degree centrality is calculated by Equation 4.1.

$$\boldsymbol{C_D(n_i) = d(n_i) = \sum_j A_{ij}} \qquad \textbf{(4.1)}$$

where i is the focal node, j is all other nodes, $C_D(n_i)$ is the degree centrality of node i, $d(n_i)$ is the number of lines associated with node i, and A denotes the adjacency matrix. Aij = 1 if node i is connected to node j, and 0 otherwise.

Closeness centrality helps to identify a word that plays a geographic center of the network. Based on closeness centrality, it can be interpreted as the key consumer value that a particular word has the shortest distance to all of other words within the network. The closeness centrality is calculated by Equation 4.2.

$$\boldsymbol{C_c(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1}} \qquad \textbf{(4.2)}$$

where g is the group size, i is the focal node, j is all other nodes, $C_C(n_i)$ is the closeness centrality of node i, and d (n_i, n_j) denotes the number of lines in the geodesic linking nodes i and j.

Closeness centrality defines the importance of a node as the length in links of the shortest path from one node to the other node, by calculating the sum of graph-theoretic distances from all other nodes (Freeman, 1979).

It is an index of efficiency of a node, the opportunity to obtain new information earlier than other nodes in the network, by measuring the expected time until information arrives flowing through the network (Borgatti, 2005; Freeman, 1979).

Betweenness centrality helps to identify a word that acts as a mediator in the network. Based on betweenness centrality, it can be considered as the key consumer value that a particular word plays the important role in bridging between different groups of words. The betweenness centrality is calculated by Equation 4.3.

$$\boldsymbol{C_B(n_i) = \sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}}} \qquad \textbf{(4.3)}$$

where g is the group size, i is the focal node, j and k are all other nodes, $C_B(n_i)$ is the betweenness centrality of node i, g_{jk} denotes the number of geodesics connecting node j and node k, and $g_{jk}(n_i)$ denotes the number of geodesics linking node j and node k that contain node i.

Betweenness centrality defines the importance of a node by calculating the number of geodesic paths that pass through a given node. Whereas closeness centrality is based on the length between nodes, betweenness centrality is an index of information control that focuses on the frequency of nodes in the shortest paths between nodes.

Eigenvector centrality helps to identify a word with a large number of the weighted connections consisted of direct and indirect linkages to other words. The weighted connection is derived based on the eigenvector of adjacency matrix from the network (Bonacich, 1972). According to eigenvector centrality, it can be interpreted as the key consumer value that a particular word has both the highest frequency of simple connections with other words and connections with the associated words in the network. The eigenvector centrality is calculated by Equation 4.4.

$$\boldsymbol{Av = \lambda v} \qquad (4.4)$$

where v is the eigenvector, λ is the eigenvalue, and A denotes the adjacency matrix of the graph.

Whereas degree centrality only considers the number of directed links a word has, eigenvector centrality defines the importance of a word as the number of undirected links with the associated words, as well as directed links, in terms of the global centrality of the network (Borgatti, 2005). Thus, eigenvector centrality aims to capture the qualified popularity of a particular word.

4.1.2. Results

Network analysis was carried out based on UCINET 6.0 and Netdraw 2.0, by utilizing one-way and weighted matrixes. The minimum cut-off value was 2. In both hierarchical and non-hierarchical methods, data were analyzed in terms of the entire user group and its sub-groups including "fashion," "celebrities," and "game." The data from the entire user group were resulted in the overall network, which is the sum of the data from fashion, game, and celebrity user groups.

Network analysis in this study paid attention to the comparison of the key user value in the overall network and its sub-groups network derived by hierarchical and non-hierarchical processing methods, based on network centrality measures such as degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. Each network of user group was illustrated in Figures 4.2 and 4.3, and detailed illustrations were attached in Appendix C.

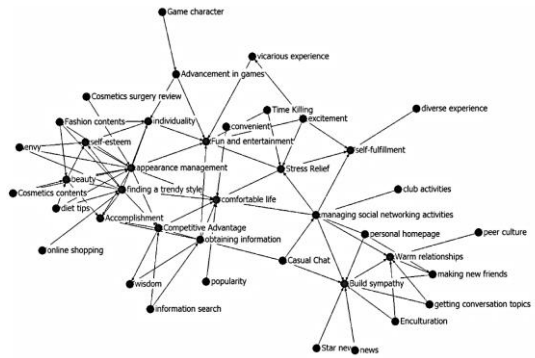
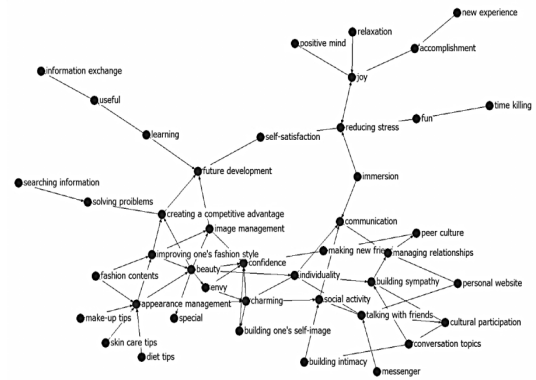
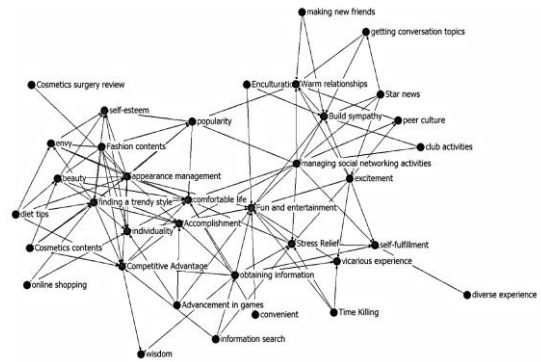
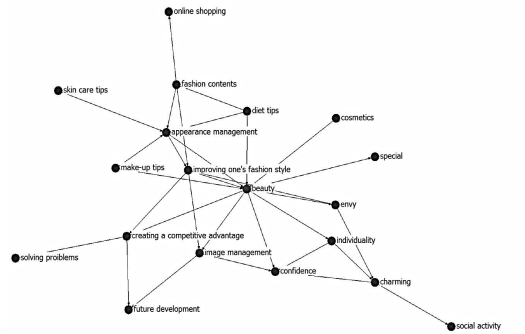
	Hierarchical Data Analysis	Non-Hierarchical Data Analysis
Overall (cutoff value=5)		
Fashion (cutoff value=3)		

Figure 4.2 Network of user groups (a)

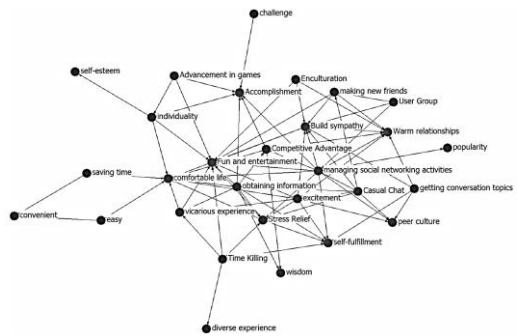
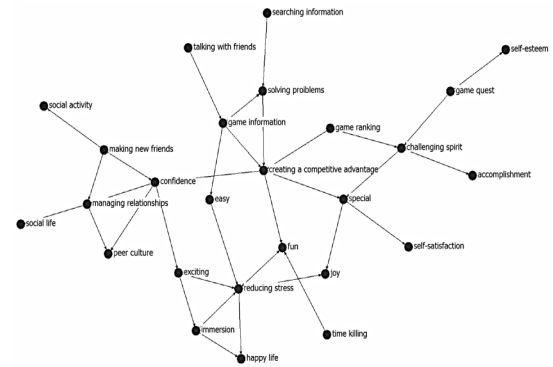
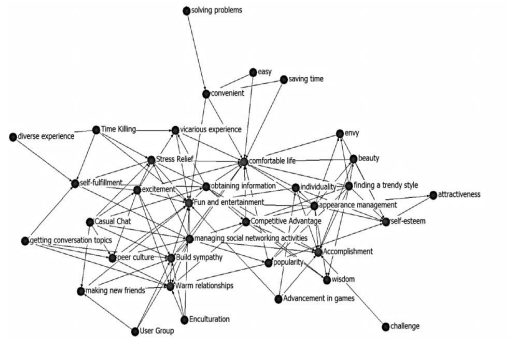
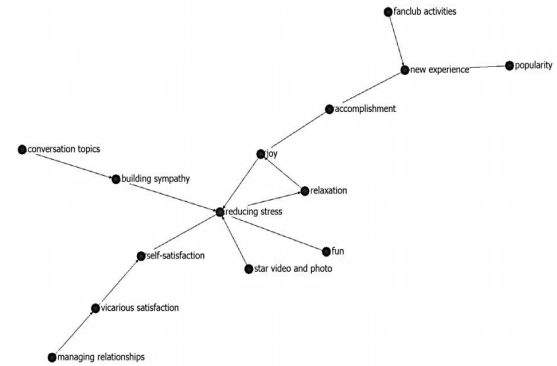
	Hierarchical Data Analysis	Non-Hierarchical Data Analysis
Game (cutoff value=2)		
Celebrity (cutoff value=2)		

Figure 4.3 Network of user groups (b)

Hierarchical method

As shown in Figures 4.2 and 4.3, the key user values based on hierarchical processing method were "warm relationships," "fun and entertainment," "build sympathy," and "comfortable life" in the network generated by the data for the entire user group. The networks according to the interests of the users were also illustrated in Figures 4.2 and 4.3.

For the fashion context, the major keywords were "comfortable life," "fun and entertainment," "warm relationships," and "build sympathy". In the network for the users who are interested in game, "fun and entertainment," "comfortable life," "build sympathy," and "stress relief" were emerged as the important keywords. In terms of celebrity related topics, the key user values were "fun and entertainment," "warm relationships," "comfortable life," "build sympathy."

According to degree centrality, a word with the highest number of direct links to other words was "warm relationships" as shown in Table 4.1. "Warm relationships" showed the highest degree centrality normalized value of 4.394 for the entire user group, as well as for its sub-groups related to fashion, game, and celebrity. It can be interpreted that most of the other words in the network have a direct link with "warm relationships."

Table 4.1 Key user values by a hierarchical data analysis based on degree centrality

Components	Normalized value	Term
All consumers	4.394	Warm relationships
	4.232	Fun and entertainment
	3.342	Build sympathy
Fashion	4.394	Warm relationships
	4.232	Fun and entertainment
	3.181	Comfortable life
Game	4.394	Warm relationships
	4.232	Fun and entertainment
	3.181	Comfortable life
Celebrity	4.394	Warm relationships
	4.232	Fun and entertainment
	3.181	Comfortable life

Table 4.2 Key user values by a hierarchical data analysis based on closeness centrality

Components	Normalized value	Term
All consumers	6.066	Comfortable life
	5.733	Fun and entertainment
	5.691	Self-esteem
Fashion	2.689	Comfortable life
	2.622	Fun and entertainment
	2.614	Self-esteem
Game	2.620	Comfortable life
	2.556	Fun and entertainment
	2.548	Self-esteem
Celebrity	3.302	Comfortable life
	3.201	Fun and entertainment
	3.189	Self-esteem

In terms of closeness centrality, a word acting as the geographic center of the network was "comfortable life" as shown in Table 4.2. "Comfortable life" revealed as the keyword with the highest in-closeness centrality value for the entire user group. This keyword was also important to users who are interested in fashion and celebrities. It can be interpreted that "comfortable life" has an ability to easily connect to other words within the network.

According to betweenness centrality, a word playing as a mediator in the network was "excitement" for the entire user group as shown in Table 4.3. "Excitement" showed the highest betweenness centrality normalized value of 1.631. For fashion and celebrity context, "managing social networking activities" was emerged as the keyword with the highest betweenness centrality value. This means that "excitement" and "managing social networking activities" play an important role in controlling the information flow in the network.

In terms of eigenvector centrality, a word both with the highest number of direct and indirect links to other words was "warm relationships" as shown in Table 4.4. "Warm relationships" showed the highest eigenvector centrality for the entire user group, as well as for its sub-groups related to fashion, game, and celebrity. In Table 4.4, "warm relationships" has the eigenvector centrality normalized value of 67.998 in the network from the data for the entire user group. It can be interpreted that 68% of other words in the network have a link with "warm relationships."

Table 4.3 Key user values by a hierarchical data analysis based on betweenness centrality

Components	Normalized value	Term
All consumers	1.631	Excitement
	1.459	Managing social networking activities
	1.331	Obtaining information
Fashion	0.521	Managing social networking activities
	0.400	Obtaining information
	0.315	Appearance management
Game	0.649	Excitement
	0.309	Stress relief
	0.239	Challenge
Celebrity	1.055	Managing social networking activities
	0.745	Obtaining information
	0.602	Excitement

Table 4.4 Key user values by a hierarchical data analysis based on eigenvector centrality

Components	Normalized value	Term
All consumers	67.998	Warm relationships
	66.954	Build sympathy
	58.832	Managing social networking activities
Fashion	70.855	Warm relationships
	66.425	Build sympathy
	56.94	Managing social networking activities
Game	74.014	Warm relationships
	70.151	Build sympathy
	60.678	Managing social networking activities
Celebrity	70.951	Warm relationships
	68.935	Build sympathy
	59.762	Managing social networking activities

Non-hierarchical method

As shown in Figures 4.2 and 4.3, the key user values based on non-hierarchical processing method were "warm relationships," "fun and entertainment," "build sympathy," and "comfortable life" in the network generated by the data for the entire user group. For the fashion context, the major keywords were appearance management," "beauty," and "confidence". In the network for the users who are interested in game, "reducing stress," "joy," and "fun" were emerged as the important keywords. In terms of celebrity related topics, the key user values were "reducing stress," "joy," and "new experience."

According to degree centrality, a word with the highest number of direct links to other words was "managing relationships" as shown in Table 4.5. "Warm relationships" showed the highest degree centrality normalized value of 3.244 for the entire user group. For game and celebrity context, "joy" has the highest degree centrality value. This means that most of the other words in the network have a direct link with "managing relationships."

In terms of closeness centrality, a word acting as the geographic center of the network was "joy" as shown in Table 4.6. "Joy" revealed as the keyword with the highest in-closeness centrality normalized value of 25.952 for the entire consumer group.

Table 4.5 Key user values by the non-hierarchical data analysis based on degree centrality

Components	Normalized value	Term
All consumers	3.244	Managing relationships
	2.949	Joy
	2.392	Reducing stress
Fashion	1.694	Beauty
	1.623	Appearance management
	1.164	Improving one's fashion style
Game	1.631	Joy
	1.58	Reducing stress
	1.07	Fun
Celebrity	2.599	Joy
	2.294	Reducing stress
	1.529	New experience

Table 4.6 Key user values by the non-hierarchical data analysis based on closeness centrality

Components	Normalized value	Term
All consumers	25.952	Joy
	25.115	Reducing stress
	24.661	Building sympathy
Fashion	1.674	Joy
	1.663	Comfort
	1.663	Relaxation
Game	1.888	Happy life
	1.863	Reducing stress
	1.863	Joy
Celebrity	1.43	Self-satisfaction
	1.381	Confidence
	1.368	Beauty

In Table 4.6, “happy life” showed the highest closeness centrality value for game context. In terms of celebrity related topics, the keyword with the highest closeness centrality value was “self-satisfaction”. This implies that “joy” has an ability to easily connect to other words within the network.

According to betweenness centrality, a word playing as a mediator in the network was “joy” for the entire user group as shown in Table 4.7 “Joy” showed the highest betweenness centrality normalized value of 11.858. For fashion and celebrity context, “building sympathy” and “reducing stress” were emerged as the keywords with the highest betweenness centrality value. This means that “joy,” “building sympathy,” and “reducing stress” play an important role in controlling the information flow in the network.

In terms of eigenvector centrality, a word both with the highest number of direct and indirect links to other words was “beauty” as shown in Table 4.8 “Beauty” showed the highest eigenvector centrality normalized value of 52.221 for the entire user group. User groups who are interested in fashion indicated “appearance management” as the important keyword. In game context, “reducing stress” showed the highest eigenvector centrality. “Joy” was the critical keyword in user groups who are interested in celebrity. It can be interpreted that 52% of other words in the network have a link with “beauty.”

Table 4.7 Key user values by the non-hierarchical data analysis based on betweenness centrality

Components	Normalized value	Term
All consumers	11.858	Joy
	6.620	Communication
	6.553	Managing relationships
Fashion	1.741	Building sympathy
	0.838	Improving one's fashion style
	0.722	Beauty
Game	1.401	Joy
	1.158	Creating a competitive advantage
	1.15	Reducing stress
Celebrity	1.836	Reducing stress
	0.977	Joy
	0.803	Peer culture

Table 4.8 Key user values by the non-hierarchical data analysis based on eigenvector centrality

Components	Normalized value	Term
All consumers	52.221	Beauty
	52.033	Appearance management
	38.438	Managing relationships
Fashion	76.278	Appearance management
	75.234	Beauty
	55.295	Improving one's fashion style
Game	87.199	Reducing stress
	71.973	Joy
	38.849	Immersion
Celebrity	61.080	Joy
	60.254	Reducing stress
	50.036	Accomplishment

4.1.3. Discussion

The results of this study showed the significant differences between the key user values derived by the hierarchical and non-hierarchical processing approaches. For example, with eigenvector centrality, "beauty" was the key value in the network generated by non-hierarchical method, whereas "warm relationships" emerged as the critical value based on the hierarchical method. These differences can provide two major empirical benefits of employing the non-hierarchical processing method for the interview data in the purpose of eliciting user's thoughts or feelings for a given product or service.

The non-hierarchical method can help to derive the key values that express the concrete characteristics of user groups, rather than using the hierarchical method. As shown in Tables 4.1, 4.2, 4.3, and 4.4, the hierarchical method resulted in no differences among the key values generated by user groups, despite the difference in the type of user groups. Rather, the key values were the same across all groups, including the entire user and users with the interest of fashion, game, and celebrity. For example, in the degree centrality analysis, whereas the hierarchical method yielded "warm relationships" as the key value regardless of the characteristics of user groups, the non-hierarchical method demonstrated "joy" as the key value in the context of game and celebrity, and "beauty" as the keyword representing the fashion related topics.

This result may be caused by the data loss due to the task of re-grouped words for constructing a particular theme, after the elimination of redundancy among similar words. As Lin (2002) stated, the hierarchical analysis approach inevitably tends to entail the simplification of relevant words during the abstraction phase. This task can help to understand the interview data with a seamless structure, but can result in grouped words with excessive abstraction.

The non-hierarchical method also helps to reflect and preserve the natural flow of user's thoughts on a given product, without restricting the connection in a vertical way. Although the hierarchical method can be useful to extract the logical flow of information (Whitlark & Allred, 2003), the user value cannot be understood only in logical aspects.

However, in traditional hierarchical method, the linkage between each word from the interview is pre-determined according to the category of each word belongs. This implies that the hierarchical method such as content analysis in laddering technique imposes the vertical linkage to themes induced by the integration of re-grouped words from the interview. For example, according to the degree and eigenvector centrality, "warm relationships" appeared as the key user value for the entire consumer group from the results of the hierarchical processing method. In contrast to this result, the non-hierarchical method generated "managing relationships" and "beauty" as the critical user value based on the degree and eigenvector centrality value. This difference can be explained by the type of connection between words in the hierarchical and no-hierarchical methods.

This study has an implication that the non-hierarchical method can be especially useful for the purpose of explaining the interview data according to the type of user groups or the components of interviews, rather than analyzing this data with the hierarchical method. Although this study has the limitation of sample size, it provided an effective example to analyze the interview data, from multiple perspectives with quantitative values, such as degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality.

4.2. Deriving common and distinct keywords

This section aims to provide a systemic way to elicit the keywords in the consideration of their common and distinct aspects for the interview components. As mentioned in Section 2.2, in user experience research, it is key to analyze the interview data based on a concrete procedure of data analysis and to provide the interpretation of those results in a simple, time-efficient, and cost-efficient manner (Bargas-Avila & Hornbæk, 2011; Vermeeren et al., 2010).

Keyword analysis techniques in text mining are generally based on the frequency and co-occurrence with other words (Lott, 2012). Calculating raw word counts is the most common and practical approach of extracting the keywords. In addition to raw word count, several frequency statistics

such as tf-idf (Salton & Buckley, 1988) or probabilistic measures (Kit & Liu, 2008) have been introduced. However, most of them may be unsuitable for analyzing short texts, because they use a large reference corpus (Boguraev & Kennedy, 1999; Chuang et al., 2012). Thus, it is needed to develop a practical way to find the essential keywords from the interview data for the user experience.

As an empirical study, Study 2 attempted to derive the informative keywords based on their common and distinct aspects, as well as the frequency ranking of words. To reveal the usefulness of the proposed approach, this study tried to understand the first impression of product sounds not only based on the unstructured interview, but also based on a questionnaire.

4.2.1. Method

Study 2 used 10 camera shutter sounds in order to understand the impression of product sounds that users have in their mind, such as smartness, friendliness, and satisfaction. The overall process of this study consists of three phases: data collection, data analysis, and data interpretation, as shown in Figure 4.4.

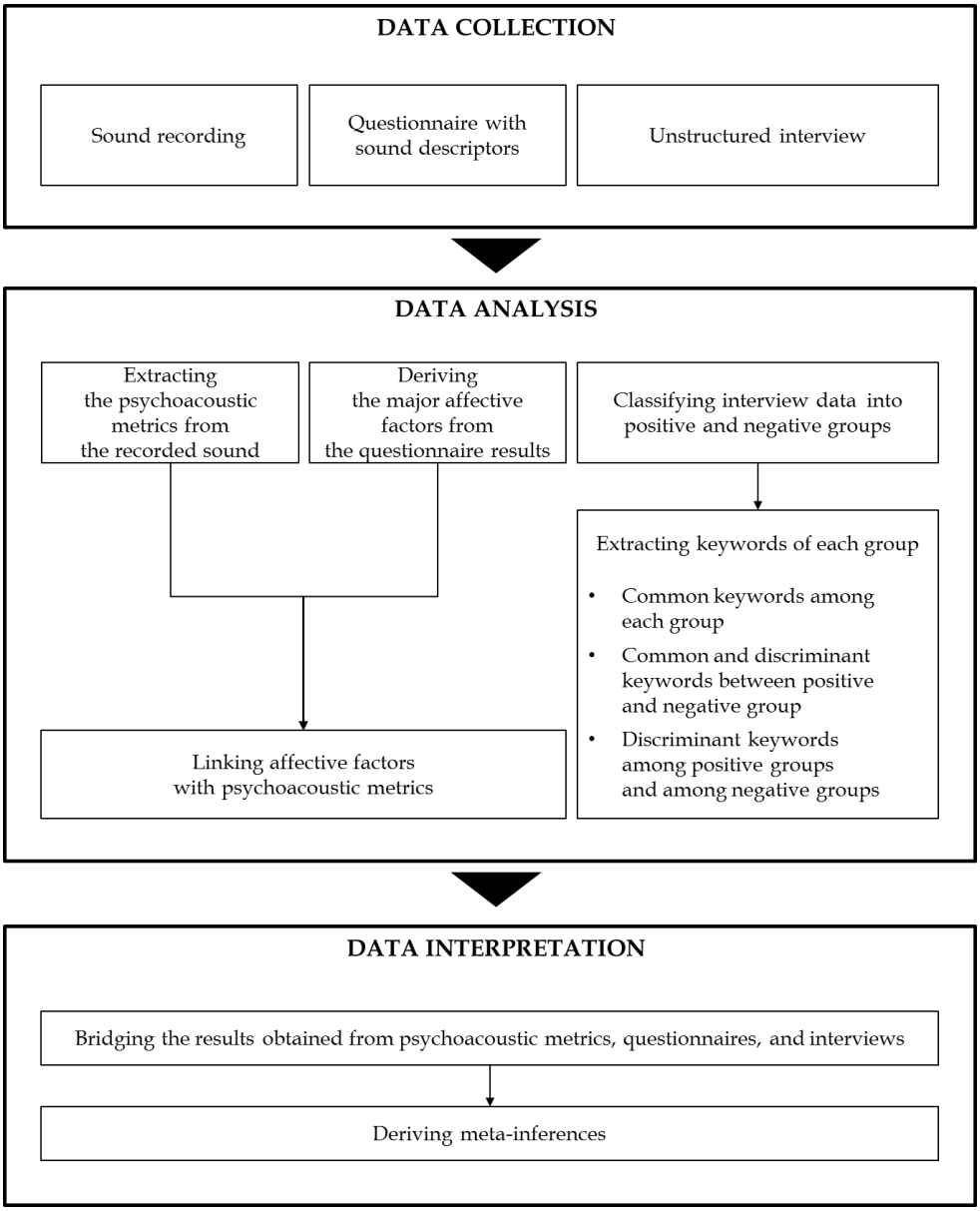


Figure 4.4 The overall process of Study 2

In the data collection phase, subjective rating on the camera shutter sound was conducted with a questionnaire based on the collection of sound descriptors. A short paper-and-pencil interview was also conducted to collect the perceived impressions for a given sound. These two types of data were collected in sequential order. Interviews were performed after completing the questionnaire for each sound. In addition to a questionnaire and interview, 10 camera shutter sounds were recorded for further analysis. The data analysis phase is consisted of three parts: analyzing the psychoacoustic metrics, deriving the main affective factors, and extracting keywords. In the data interpretation phase, meta-inferences can be drawn after merging of these findings.

Data collection

Both questionnaire and interview data were collected for 50 participants (25 male and 25 female), consisting of 28 experts and 22 ordinary people with normal hearing abilities. During 1.5 hours on average, they evaluated the 10 camera shutter sounds based on the questionnaire with sound descriptors and participated in interviews about the reasons for their evaluation of each shutter sound.

Structured data was gathered from a questionnaire with sound descriptors and sound recording. Ten shutter sounds were recorded in the anechoic chamber, and their average time were about 165ms. Prior to

performing the questionnaire, researchers should select sound descriptors with the ability to represent affective aspects of sonic experience for a product or service. Sound descriptors are usually adjectives that can help to express user's feelings and to design a questionnaire for affective evaluation.

This study collected sound descriptors, words relevant to product sounds, through a literature review on psychoacoustic research (273 adjectives), web reviews in Korean, American, European, and other websites (70 adjectives), and five experts interviews (60 adjectives). The experts were people in their twenties who had had more than five years' experience in the photo club. The elimination of redundant and similar words resulted in 218 words. Among the 218 words, the final 29 words were selected based on the expert interview with five camera sellers who have an average of 11 years of sales experience. The 29 sound descriptors were as follows: resonating, deep, heavy, strong, lingering, light, classical, balanced, harsh, fresh, pure, sophisticated, clean, modern, funny, clear, dull, noble, silent, comfortable, noisy, messy, unstable, hollow, annoying, complicated, hard, mechanical, and soft.

A questionnaire with the 29 sound descriptors was used for collecting structured data on the impression of camera shutter sounds (Appendix D). Participants, while wearing a blindfold, could hear each shutter sound twice to experience all shutter sounds in advance before they evaluate a particular sound. These sounds were generated from the cameras while they were covered with a cloth for removing the brand effect.

After the preview, participants were required to hear each shutter sound fifteen times divided into three periods and to randomly evaluate the sound based on the 29 sound descriptors using a seven-point Likert scale (1=strongly disagree, 7=strongly agree). They also evaluated how each smart, friendly, and satisfactory, each sound is, on a scale of 0 to 100. These values can be treated as perceived smartness, friendliness, and satisfaction.

Interview data was collected by a paper-and-pencil and unstructured interview at the end of the questionnaire of each shutter sound. During the interview, participants were asked to freely describe the overall impression for a given sound. No response exceeded more than three sentences.

Analysis of the affective factors from the questionnaire

Data obtained from the questionnaire were analyzed in two steps using SPSS. First, factor analysis was used for the reduction of relevant sound descriptors, and thus for generating the factors. Next, determinant analysis was employed as a tool to for investigating the factors that have a strong influence on determining the perceived smartness, friendliness, and satisfaction.

For determinant analysis, perceived smartness, friendliness, and satisfaction value were divided into positive groups (smart, friendly, and satisfactory) and negative groups (not-smart, not-friendly, and not-

satisfactory) through data dichotomization. For example, if the perceived smartness of a particular sample is over the average value of the perceived smartness for all samples, this sample is coded as 1 (smart), which can be interpreted as a positive group. Otherwise it is coded as 0 (not-smart). The same procedure applied to perceived smartness, friendliness, and satisfaction for each of the ten shutter sounds. Thus, a particular sample always has a set consisting of three codes, regarding smartness, friendliness, and satisfaction.

Analysis of the psychoacoustic metrics

This study used Loudness, Sharpness, and Roughness as psychoacoustic metrics. Loudness (N, sone) refers to the perceived intensity of a sound. It is the most influential element to determine the sound quality among other parameters. Sharpness (S, acum) is calculated based on the centroid of the signal spectrum (Lichte, 1941), and represents the perceived degree of sharpness or shrillness of the sound. Roughness (R, asper) results from rapid amplitude modulation, and is correlated with auditory dissonance. Ten camera shutter sounds were recorded to analyze psychoacoustic metrics on these sounds were calculated using PsySound3 (Cabrera, Ferguson, & Schubert, 2007). The relation between affective factors and psychoacoustic metrics was drawn by correlation analysis, using SPSS.

Analysis of keywords from the interview data

Text data from the interview were assigned to these six categories in order to provide a deep understanding of data. Depending on a set of codes assigned to a particular sample, each description of a sample belongs to three categories among smart, not smart, friendly, not friendly, satisfactory, and not satisfactory. For example, if sample 1 is classified as "not-smart," "friendly," and "satisfactory," user's description on sample 1 also has these three labels. The descriptions in six categories were not mutually exclusive. Frequency analysis was applied to extract the representative keywords from each of the six categories, using R software.

This study tried to uncover the important keywords from the interview data by comparing keywords 1) from all of positive and negative groups, 2) between positive and negative groups of each impression, and 3) within positive and negative groups. As mentioned above, positive groups refer to smart, friendly, and satisfactory categories, and negative groups are composed of not-smart, not-friendly, and not-satisfactory categories. Representative keywords of each category were defined by comparing keywords among positive groups and among negative groups, respectively. In other words, the difference of keywords among categories was captured by the elimination of co-occurring keywords in smart, friendly, and satisfactory groups. The same procedure was applied to not-smart, not-friendly, and not-satisfactory groups.

4.2.2. Results

The average time of the 10 shutter sounds were about 165ms. As shown in Figure 4.5, there was a similar tendency among the average value of perceived smartness, friendliness, and satisfaction for most samples. This can be considered to be due to their similarities. In correlation analysis, perceived smartness had a positive link with friendliness (r=0.522, p<0.01) and with satisfaction (r=0.725, p<0.01). Perceived friendliness showed a positive correlation with satisfaction (r=0.740, p<0.01). There was no significant difference between experts and ordinary people for the perceived smartness (p=0.886), friendliness (p=0.272), or satisfaction (p=0.743) of experts and ordinary people. There was also no significant difference between genders (p>0.05).

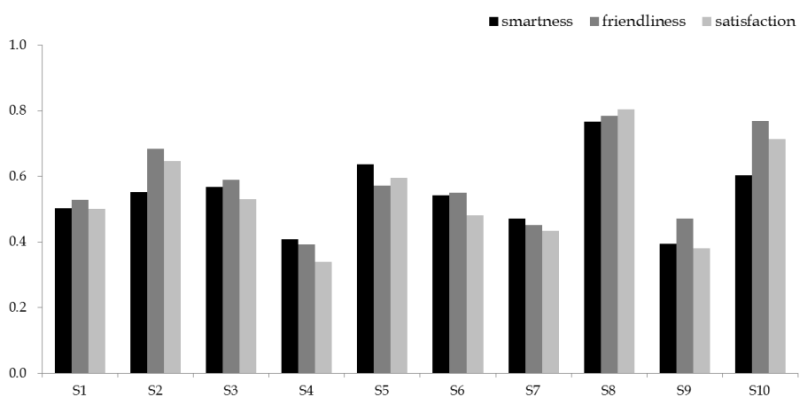


Figure 4.5 The average value of the perceived smartness, friendliness, and satisfaction for each sample sound

Results of questionnaires

Factor analysis on the 29 sound descriptors with Varimax rotation resulted in five factors, which can explain 62.51% of the variance. As shown in Table 4.9, Factor 1 can be interpreted as the deep resonance of the sound and contains resonating, deep, heavy, strong, lingering, light, classical, balanced, and harsh. Resonating and deep had a strong positive correlation with Factor 1, whereas light showed a strong negative correlation with Factor 1. Heavy, strong, and harsh were positively linked to Factor 1, as well as the degree of the balance and the classical sense of the sound. Thus, Factor 1 refers to a feeling of resonance that can be defined as not only a deep and strong sound but also a classical and balanced sound without the lightness.

Factor 2 implies a clean and uncluttered sound and includes fresh, pure, sophisticated, clean, modern, funny, clear, and dull. Sophisticated, modern, and fun were positively associated with Factor 2, as well as fresh, pure, and clean. Dull was negatively loaded on Factor 2, because clarity, a term with the opposite meaning, had a positive relation with Factor 2. Therefore, Factor 2 represents a clean, uncluttered sound.

Factor 3 is related to the calmness of the sound and involves noble, silent, comfortable, and noisy. As predicted, noisy negatively loaded on Factor 3, whereas the other descriptors had a positive relation with Factor 3.

Table 4.9 Factor analysis of sound descriptors

Components	Items	Loading
Factor 1	resonating	0.827
	deep	0.824
	heavy	0.747
	strong	0.744
	lingering	0.744
	light	-0.731
	classical	0.693
	balanced	0.475
	harsh	0.446
Factor 2	fresh	0.780
	pure	0.761
	sophisticated	0.726
	clean	0.703
	modern	0.631
	fun	0.584
	clear	0.562
	dull	-0.539
Factor 3	noble	0.741
	silent	0.719
	comfortable	0.574
	noisy	-0.537
Factor 4	messy	0.649
	unstable	0.599
	hollow	0.574
	annoying	0.552
	complicated	0.506
Factor 5	hard	0.808
	mechanical	0.635
	soft	-0.546

Factor 4 deals with the congestion of the sound and contains messy, unstable, hollow, annoying, and complicated. All of these words, which are typically treated as negatives, were positively connected with Factor 4. It is interesting that complicated was also grouped in Factor 4 with annoying and messy. This can be interpreted as indicating that participants tended to judge a complicated sound as a messy and annoying one and to evaluate hollow as indicating a distinct feeling from resonating and lingering, which are loaded on Factor 1.

Factor 5 implies the mechanical hardness of the sound and includes hard, mechanical, and soft. Soft had a negative correlation with Factor 5, since it is related to the low flexibility of the sound. Participants treated the feeling of hard as similar to mechanical feelings.

With the five factors derived above as the independent variables, and the three impressions (perceived smartness, friendliness, and satisfaction) as the grouping variables, the discriminant analysis was conducted to identify the relative importance of each of the five affective factors, which can determine the perceived smartness, friendliness, and satisfaction induced by camera shutter sounds. Based on the stepwise method, the discriminant functions obtained for each grouping variables were significant: smartness (Wilks' Lambda=0.65, Chi-square=215.29, df=3, $p<0.001$), friendliness (Wilks' Lambda=0.59, Chi-square=261.65, df=5, $p<0.001$), and satisfaction (Wilks' Lambda=0.52, Chi-square=326.02, df=5, $p<0.001$).

Table 4.10 demonstrates the standardized canonical discriminant coefficients and the structure coefficients for each of grouping variables. These two coefficients indicate the relative importance of each independent variable to decide the groups of the dependent variable to which they belong. However, researchers disagree over which of these values is more valid; thus, this study considered both coefficients for a comprehensive understanding.

For the sounds perceived as smart, the relative importance of Factor 2 was higher than Factor 3 and Factor 1 according to both the standardized coefficient and the structure coefficient. The discriminatory abilities of Factor 3 and Factor 1 were similar. Factor 4 and Factor 5 were excluded to generate the discriminant function for smart sounds. Similar to the aforementioned results, the determination of satisfactory sounds was most impacted by Factor 2, but Factor 1 was more important than Factor 3 in terms of the standardized coefficient and the structure coefficient. For friendly sounds, Factor 1 has the most critical variable compared to Factor 2 and Factor 3.

Table 4.10 The relative importance of affective factors

	Smartness		Friendliness		Satisfaction	
	standardized canonical coefficient	structure coefficient	standardized canonical coefficient	structure coefficient	standardized canonical coefficient	structure coefficient
Factor 1	0.42	0.29	0.80	0.59	0.73	0.45
Factor 2	0.92	0.80	0.58	0.37	0.82	0.55
Factor 3	0.45	0.31	0.47	0.29	0.48	0.26
Factor 4	-	0.05	-0.26	-0.16	-0.29	-0.15
Factor 5	-	0.05	-0.46	-0.29	-0.32	-0.17

Note: the structure coefficients of Factor 4 and 5 for smartness were not significant.

Results of psychoacoustic metrics

Loudness, Sharpness, and Roughness for each of the 10 sound samples were used for analyzing the correlation between the five factors and psychoacoustic metrics, and between perceived smartness, friendliness, and satisfaction and psychoacoustic metrics. Several values related to Loudness, Sharpness, and Roughness were calculated to reflect the time-varying characteristics of sounds, including the average, median (the 50th percentile), minimum, maximum, 5th percentile, 10th percentile, and 90th percentile.

Table 4.11 represents the correlation between single values of psychoacoustic metrics and the five factors. Factor 1, a deep resonance, had a negative correlation to single values, and it showed a relatively strong correlation to the 5th percentile Loudness (N_5), the median Sharpness (S_{50}), the 5th percentile Roughness (R_5), the 10th percentile Roughness (R_{10}), and the minimum Roughness (R_{min}) compared to the other factors.

As shown in Table 4.11, the best correlated values to Factor 2 were the average Loudness (N_{ave}) and the 90th percentile Sharpness (S_{90}). Factor 3 was correlated positively to most of the values, but especially to the average Roughness (R_{ave}).

Table 4.11 Correlation between affective factors and psychoacoustic metrics

		Factor1	Factor2	Factor3	Factor4	Factor5
Loudness related values	N_5	-.485**	-.183**	.230**	.005	-.175**
	N_{10}	-.457**	-.176**	.239**	-.008	-.177**
	N_{50}	-.441**	-.188**	.224**	-.005	-.177**
	N_{90}	.477**	.107*	.039	-.069	-.008
	N_{min}	-.281**	-.058	.236**	-.096*	-.058
	N_{max}	-.271**	-.156**	.074	-.045	.177**
	N_{ave}	-.288**	-.314**	.253**	-.017	-.097*
Sharpness related values	S_5	-.446**	.132**	.153**	-.054	-.015
	S_{10}	-.465**	.018	.085	.019	.008
	S_{50}	-.580**	.008	.186**	-.003	-.048
	S_{90}	-.009	.249**	-0.06	-.056	.152**
	S_{min}	-.281**	-.058	.236**	-.097*	-.058
	S_{max}	-.259**	.049	-.071	.001	.207**
	S_{ave}	-.465**	.019	.113*	-.024	.114*
Roughness related values	R_5	-.526**	-.163**	.292**	-.061	-.133**
	R_{10}	-.526**	-.163**	.292**	-.061	-.133**
	R_{50}	-.320**	-.104*	.250**	-.086	-.091*
	R_{min}	-.526**	-.163**	.292**	-.061	-.133**
	R_{ave}	-.310**	-.021	.335**	-.165**	-.047

Note: *=significant at the 0.05 level, **=significant at the 0.01 level.

Table 4.12 describes the correlation between psychoacoustic metrics and the perceived smartness, friendliness, and satisfaction. As shown in Table 4.12, although the correlation strength between Loudness-related values and the perceived smartness, friendliness, and satisfaction was not high, the direction of relationship between the 5th percentile Loudness (N_5) and the perceived smartness, friendliness, and satisfaction was significantly opposite to the relationship between the 90th percentile Loudness (N_{90}) and

the perceived smartness, friendliness, and satisfaction. A similar phenomenon has been found in the relation with Factor 1 and N_5, N_{10}, and N_{90}. The 5th percentile, 10th percentile, and 90th percentile Loudness each affected Factor 1 with a relatively strong influence compared to the average of Loudness (N_{ave}).

Table 4.12 Correlation between psychoacoustic metrics and the perceived smartness, friendliness, and satisfaction

		Smartness	Friendliness	Satisfaction
Loudness related values	N_5	-.154**	-.203**	-.255**
	N_{10}	-.139**	-.178**	-.231**
	N_{50}	-.148**	-.180**	-.236**
	N_{90}	.240**	.286**	.336**
	N_{min}	-.002	-.030	-.062
	N_{max}	-.098*	-.173**	-.198**
	N_{ave}	-.141**	-.162**	-.222**
Sharpness related values	S_5	-.010	-.109*	-.108*
	S_{10}	-.105*	-.220**	-.224**
	S_{50}	-.104*	-.216**	-.236**
	S_{90}	.151**	.036	.112*
	S_{min}	-.002	-.030	-.062
	S_{max}	-.045	-.168**	-.143**
	S_{ave}	-.060	-.213**	-.204**
Roughness related values	R_5	-.117**	-.173**	-.228**
	R_{10}	-.117**	-.173**	-.228**
	R_{50}	-.034	-.060	-.101*
	R_{min}	-.117**	-.173**	-.228**
	R_{ave}	.063	.022	-.004

Note: *=significant at the 0.05 level, **=significant at the 0.01 level.

Results of interviews

The results of frequency analysis were shown in Table 4.13, and the cut-off value was 10. The top 5 keywords of 6 categories were compared to outline the characteristics of keywords in each category. Words such as "clear," "clean," "mechanical," "silent," and "classical" were derived as the top five keywords in smart, friendly, and satisfactory groups. Similarly, the top four keywords in the not smart, not friendly, and not satisfactory groups were all the same: "mechanical," "clear," "dull," and "clean."

Keywords such as "clean," "clear," "mechanical," and "silent" appeared over six categories with a high frequency. This means that people tend to assess sounds induced by a product in terms of whether they are clean, clear, mechanical, and silent or not. These facts have a considerable relation with the results of discriminant analysis, in which a clean and uncluttered factor and a calm factor played a significant role in classifying the perceived smartness, friendliness, and satisfaction of sounds.

The similarity and difference between groups related to smartness, friendliness, and satisfaction was also drawn. For example, keywords in smart and not smart groups were merged together; then, the matching keywords were categorized as common keywords, and the rest were defined as keywords indicating the difference between the groups.

Table 4.13 Keywords relevant to smartness, friendliness, and satisfaction

Smartness				Friendliness				Satisfaction			
Smart		**Not-smart**		**Friendly**		**Not-friendly**		**Satisfactory**		**Not-satisfactory**	
Term	**Freq.**	**Term**	**Freq.**	**Term**	**Freq.**	**Term**	**Freq.**	**Term**	**Freq.**	**Term**	**Freq.**
clear	38	mechanical	34	clean	36	mechanical	33	mechanical	34	mechanical	30
clean	37	clear	26	clear	34	clear	28	clear	24	clear	25
mechanical	33	dull	23	mechanical	32	dull	22	dull	23	dull	21
silent	28	clean	20	classical	27	clean	17	clean	20	clean	17
classical	24	light	18	silent	27	silent	16	silent	18	silent	16
cheerful	20	silent	17	cheerful	22	light	13	light	18	strong	12
suitable	20	friendly	12	dull	22	strong	13	comfortable	13	friendly	11
lingering	19	comfortable	12	friendly	20	simple	12	friendly	12	harsh	11
friendly	19	harsh	10	light	19	harsh	11	annoying	10	annoying	10
modern	16			suitable	17	friendly	11	fun	10	comfortable	10
resonant	15			lingering	15	messy	10				
heavy	14			heavy	14	comfortable	10				
light	14			modern	14						
sophisticated	13			comfortable	13						
comfortable	12			stable	13						
simple	12			balanced	13						
strong	12			resonant	13						
dull	11			familiar	13						

balanced	11	sophisticated	12
stable	10	strong	12
		deep	10
		old	10
		clean	36

As shown in Table 4.14, “light,” “mechanical,” “clean,” “dull,” “friendly,” “calm,” “comfortable,” and “clear” appeared simultaneously in smart and not-smart groups. The results of friendliness- and satisfaction-related groups were similar to those of smartness-related groups.

The difference was a keyword with “strong” in friendliness-related groups and “annoying” in place of “light” in satisfaction-related groups. The common keywords within friendliness-related groups consisted of nine keywords such as “light,” “strong,” “mechanical,” “clean,” “dull,” “clear,” “friendly,” “calm,” and “comfortable.” The similarity within satisfaction-related groups could be described as the composition of “mechanical,” “clean,” “dull,” “clear,” “friendly,” “calm,” “annoying,” and “comfortable.” It is interesting that “friendly” emerged as a common keyword from all groups.

The difference within smartness-related groups could be defined with a set of keywords consisted of “strong,” “harsh,” “cheerful,” “classical,” “balanced,” “simple,” “heavy,” “sophisticated,” “stable,” “lingering,” “resonant,” “suitable,” and “modern.” For friendliness related groups, “deep,” “messy,” “old,” and “familiar” were added instead of “strong,” unlike the results of smartness-related groups.

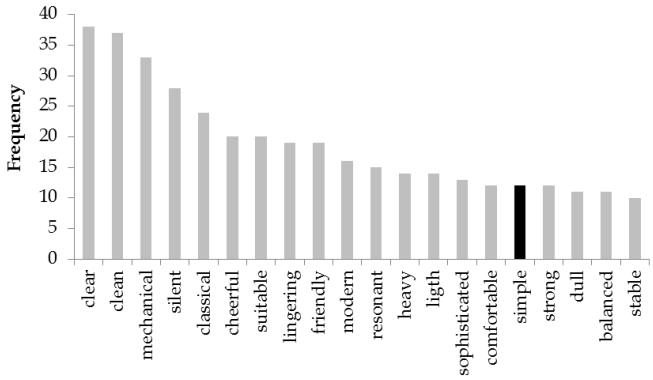
Table 4.14 The common and distinct keywords between positive and negative groups

Smartness (smart vs. not-smart)		Friendliness (friendly vs.-not friendly)		Satisfaction (satisfactory vs. not-satisfactory)	
Common keywords	**Distinct keywords**	**Common keywords**	**Distinct keywords**	**Common keywords**	**Distinct keywords**
clean	balanced	clean	balanced	annoying	fun
clear	cheerful	clear	cheerful	clean	harsh
comfortable	classical	comfortable	classical	clear	light
dull	harsh	dull	harsh	comfortable	strong
friendly	heavy	friendly	messy	dull	
light	lingering	light	simple	friendly	
mechanical	modern	mechanical	deep	mechanical	
silent	resonant	silent	familiar	silent	
	simple	strong	heavy		
	sophisticated		lingering		
	stable		modern		
	strong		old		
	suitable		resonant		
			sophisticated		
			stable		
			suitable		

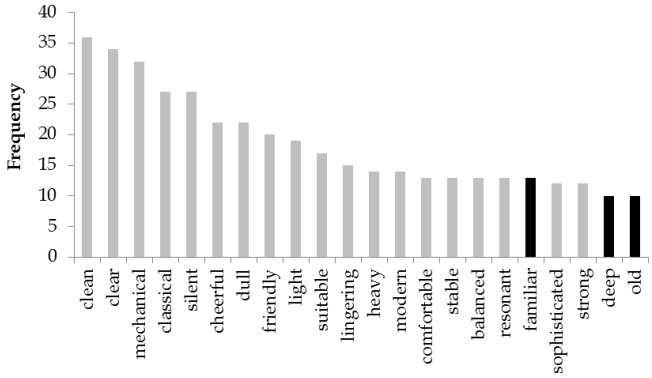
Four keywords such as “light,” “strong,” “harsh,” and “fun” were interpreted as the difference within satisfaction-related groups. To sum up, “harsh” appeared only in the negative groups, such as not smart, not friendly, and not satisfactory groups. “Suitable” emerged only in smart and friendly groups. “Classical” was shown in smartness- and friendliness-related groups, but not satisfaction related groups.

“Simple” was extracted as a distinct keyword representing the characteristics of the perceived smartness of camera shutter sounds. A friendly sound could be described as keywords with “familiar,” “deep,” and “old.” For a satisfactory sound, “annoying” and “fun” were derived as two distinct keywords. In the latter case, there were no significant keywords related to a not smart sound, but “simple” and “messy” were revealed as distinct keywords in a not friendly group. Similar to the results of the satisfactory group, “annoying” had an important role in explaining the uniqueness of a not satisfactory sound compared to not smart and not friendly sounds.

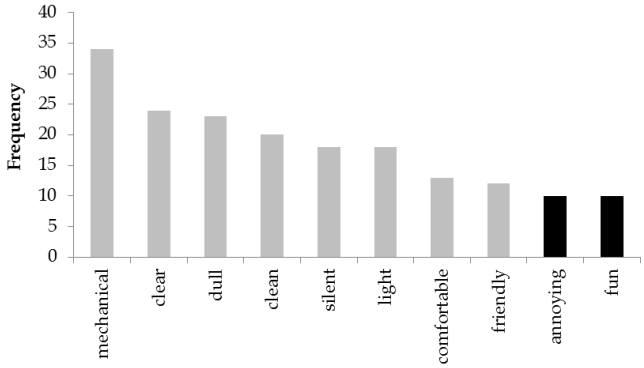
These facts also indicate that a distinct keyword was ranked lower with a relative low frequency than others. Figure 4.6 is a set of bar graphs based on keyword frequency of each positive group and helps to understand this tendency in a visual way. The bars painted in dark colors in each graph indicate the distinct keywords from positive groups.



(a) Keywords of smart group



(b) Keywords of friendly group



(c) Keywords of satisfactory group

Figure 4.6 Visualization of keywords of smart, friendly, and satisfactory groups

4.2.3. Discussion

People tended to consider that smartness, friendliness, and satisfaction have relatively high correlations with each other. In accordance with the correlation analysis, there was a substantial similarity among top-ranked keywords from the six categories (smart, not smart, friendly, not friendly, satisfactory, and not satisfactory). Despite the overlap among three impressions, it was shown that people have their obvious criterion to distinguish each impression of the product sound.

The perceived smartness was defined by clean and uncluttered characteristics of sounds, whereas the perceived friendliness was mainly described by deep and resonant characteristics of sounds. The deep and resonant factor was relatively more affected by the peak and the end of Loudness (N_5, N_{10}, and N_{90}) than by the average value of Loudness (N_{ave}). This can be explained by the peak-end rule, that means people tend to judge an experience based on its peaks and ends, rather than based on the average perception of the experience (Kahneman et al., 1993). People treated feelings of simple and messy as major features of the not friendly sound. A comparison of keywords related to smartness and friendliness also provided an opportunity to ensure the influence of those two factors on the decision of smartness and friendliness of product sounds. Most of the top-ranked keywords in smart and friendly categories were relevant to sound descriptors loaded on the clean and uncluttered factor and the deep and resonant factor, such as “clear,” “clean,” “mechanical,” “silent,” and “classical.”

However, the distinct keywords were revealed by a lower-ranked keyword based on the elimination of redundancy among positive groups (smart, friendly, and satisfactory) and among negative groups (not smart, not friendly, and not satisfactory). In people's mental model, a sense of simple played a significant role in determining the impression of smartness on camera shutter sounds, whereas the friendly impression was dominated by feelings of deep, old, and familiar. Rather, people treated feelings of simple and messy as a major feature of the not friendly group. This fact may support the results from psychoacoustic analysis that the deep and resonant factor was relatively more correlated with Roughness values than with the clean and uncluttered factor.

On the other hand, the perceived satisfaction was mainly influenced by the clean and uncluttered factor and the deep and resonant factor in similar proportions. The difference between positive and negative groups related to the satisfaction was negligible, compared to that related to the smartness and friendliness. This means that most people consider a satisfactory sound and a not satisfactory sound to share similar properties. For this reason, a distinct keyword was derived from the similarity between the positive group (satisfactory) and the negative group (not satisfactory), whereas the distinct keywords of smartness and friendliness occurred in the difference between the positive group and the negative group. Annoyance appeared as a distinct keyword that determines the characteristics both of the satisfactory group and the not satisfactory group. Thus, the elimination of annoyance in a target sound may help to increase

the clean and uncluttered factor and the deep resonance. This result indicates that people think satisfaction with the product sound can be obtained by removing the negative feelings rather than by adding something good. This fact is an obvious example that explains why the annoyance of a sound has been a central concern of previous studies in the field of sound design (Fields & Walker, 1982; Lyon, 2003).

Study 2 revealed that extracting the common and distinct keywords can help to understand people's mental model rather than relying only on the raw word counts. The comparison of top-ranked keywords had a relationship with the results of determinant analysis on the perceived impressions. This means that identifying top-ranked keywords of a specific category can help to extract the common perceptions on a product. For example, based on determinant analysis, the perceived smartness and friendliness, smartness was defined by a clean and uncluttered characteristic of sounds, whereas friendliness was mainly described as a deep and resonant characteristic of sounds.

A comparison of top keywords related to smartness and friendliness also provided an opportunity to ensure the influence of those two factors on the ascription of smartness and friendliness the product sounds. Most of top ranked keywords in smart and friendly categories were relevant to sound descriptors loaded on the clean and uncluttered factor and the deep and resonant factor, such as "clear," "clean," "mechanical," "silent," and "classical." The common keywords of each category also played a similar role as the top-ranked keywords.

Study 2 also revealed that the distinct keywords can be derived by a lower-ranked word based on the elimination of redundancy among positive groups (smart, friendly, and satisfactory) and among negative groups (not smart, not friendly, and not satisfactory). Lower-ranked keywords can serve as a clue to represent the impression of the product sound; therefore, they may allow distinguishing between one impression and another. According to Luhn (1958), words with high or low frequencies are useless for discriminating documents or contents. He asserted that words with medium frequencies have a strong discriminating power compared to those with high or low frequencies. The results of this study are partly consistent with this theory. Top-ranked words with high frequencies were not suitable for identifying discriminatory features of a particular impression describing the product sound.

However, in this study, the distinct keywords were lower-ranked words that have a relative low frequency. This is considered due to the disregard of words with less than ten frequencies from the analysis. Nevertheless, the important fact is that lower-ranked words from user interviews can play a significant role in distinguishing between specific impressions of the product. This phenomenon is similar to the Long Tail effect, according to which an area with a low occurrence probability can have a significant meaning (Anderson, 2006).

This study has several limitations in terms of the sequences of data collection and the small size of interview data compared with of questionnaire data. Nevertheless, it revealed the general ability of

purposed comparison strategy to draw in intrinsic values or the details related to the user experience of a specific product, through the empirical study. This study revealed that the proposed strategy can serve as a tool to capture a common perception on a product by analyzing top ranked keywords from the interview and identifying the similarities among interview categories. They also play a similar role to questionnaire results in structured data. The difference among interview categories can help to extract the representative information from the interview.

Further research with a large amount of unstructured text data is necessary to confirm the generalization of the purposed method to extract keywords from the interview. Further research with the different sequence of data collection is also needed to examine the effect of the sequence. The data can be obtained sequentially or concurrently.

4.3. Summary

Studies 1 and 2 provided the practical examples to overcome the main issues that should be considered in the design of data analysis. Study 1 showed that the non-hierarchical processing method may be suitable for deriving the keywords according to the characteristics of user groups or interview components, compared to the hierarchical method. Study 2 revealed that the common and distinct keywords can be extracted by

comparing a list of keywords of each category. This study also demonstrated that interview data can have an ability to explain the results obtained from the questionnaire in a systemic way, using the keywords comparison approach for deriving the common and distinct keywords. Thus, these findings obtained from Studies 1 and 2 will be employed for analyzing the interview data collected through FIEM.

Chapter 5.

EMPIRICAL VALIDATION OF FIEM

The focus of this chapter is two-fold. The first is to detail the purposed method, and to provide a systemic process to analyze and interpret the data obtained from FIEM, using empirical data. The second is to verify the effectiveness of FIEM, by comparing the results obtained from FIEM and from user reviews. Study 3 was conducted on the basis of this focus. In Study 3, the interview data was collected in accordance with the data collection procedure described in Chapter 3. This interview was consisted of four main constructs: before-, during-, and after-use impressions, and the user's underlying frame. The unstructured text data gathered from the semi-structured interview were summarized as keywords. These keywords were interpreted by their ranking based on the percentage of interviews in which a keyword appears, and the common and distinct characteristics of before-, during-, and after-use impressions.

5.1. Method

The overall process of Study 3 is composed of data collection and data analysis phases, as shown in Figure 5.1. The data for FIEM were gathered from semi-structured and in-depth interviews, in terms of four components (before-, during-, and after-use impressions, and the underlying frame) for the product. To compare the results of FIEM, Amazon reviews relevant to the vacuum cleaners were collected. The data analysis of Study 3 consists of four main steps: non-hierarchical data processing, extracting keywords of FIEM and Amazon reviews, comparing the top keywords of FIEM and Amazon reviews, and identifying the first impression of the vacuum cleaner.

In the data analysis phase, the unstructured data obtained from the interview and user reviews were processed in a non-hierarchical manner. During the non-hierarchical processing, words extracted from text data were only grouped according to their similarity of meaning, without assuming a hierarchical categorization. The important keywords of each construct were defined as the common and distinct characteristics, as well as tf-idf scores.

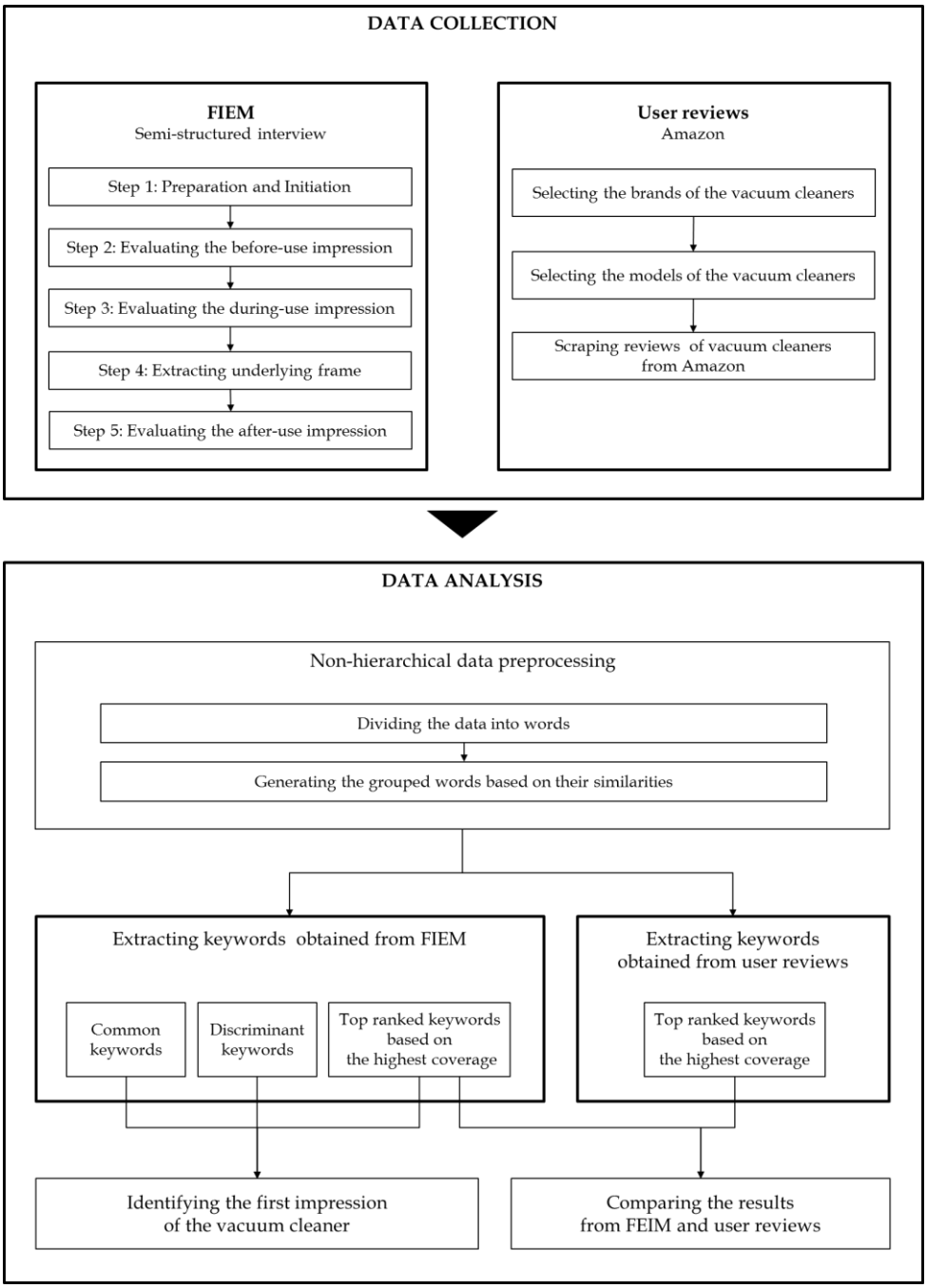


Figure 5.1 The overall process of Study 3

5.1.1. Data collection

User interviews of FIEM

In interview research, it is hard to answer the question "how many interviews are enough to generate reliable results?" According to Guest, Bunce, and Johnson (2006), the researcher can generate meaningful results with 12 interviews. This means that the data saturation occurs within 12 interviews. Supporting their claim, Galvin (2015) asserted data saturation was fairly stable after 12 interviews and definitely after 30.

Based on these references, semi-structured and in-depth interviews were performed with 20 participants, whose ages were between 39 and 57. They were all females and housewives. They were recruited through online bulletin boards. The participants' vacuum cleaner models were Samsung (35%), LG (50%), and others (15%). They used an average of 27 minutes a day of their time to clean house. To ensure the diversity of products, this study selected three types of vacuum cleaners with different colors, forms, and brands. These vacuum cleaners were used for collecting the interview data.

FIEM consists of the descriptions of the before-use impression, think-aloud data of actual use, the descriptions of underlying frame (including meanings, roles, and episodes relevant to the product), and the sketching of ideal type and the descriptions of the product characteristics to

recommend the product to their friends (Appendix E). The interviews with these four sessions were a maximum length of 1.5 hours.

When participants entered the laboratory, the researchers explained briefly about the interview they were to participate in. Before using the cleaner, the researcher asked the participant to look around briefly within five minutes as if they are shopping in the store and to freely describe their feelings or thoughts when they first saw these three products. Participants were also required to rank the products depending on their first impressions. In the next session, they were allowed to try the products according to the above ranking and to say any thoughts that came to their minds while cleaning the bookshelves, sofas, and floors with the selected product.

After use of the three cleaners, the participants were asked to answer the questions: "What do you think about the role of the cleaner and the meaning of the cleaning?", "What are the advantages and disadvantages of the cleaner you currently have in your house?", and "What are your memorable episodes with a cleaner?" In the final session, the researcher handed out an illustration of the cleaner painted with lines and without colors, and asked the participant to point out the parts to be improved in the illustration by describing what they believe to be the ideal for of cleaner you think and how the cleaner should change with simple sketches of their ideas. During this activity, the researcher advised the participants to assume that anything can be implemented technically. The participants were also asked to describe what to consider when they give a

cleaner to their friends as a gift. All verbalization during the interview was recorded and transcribed.

User reviews of Amazon

Amazon reviews for canister vacuum cleaners were collected to ensure the generality of the results obtained from FIEM. The total number of reviews collected was 918, covering 11 models and 6 brands. These models were chosen based on the popularity and brand. They are listed as follows: DC39-Animal-canister-cleaner (Dyson), DC39-Multi-floor-canister (Dyson), DC47-Animal-Compact-Canister (Dyson), UltraActive-DeepClean-Canister-EL4300B (Electrolux), Bagless-Canister-Cleaner-22614 (Kenmore), MC-CL935-Canister-Vacuum-Cleaner (Panasonic), Bagless-Canister-Vacuum-Black (Samsung), Bagless-Canister-Vacuum-Champagne (Samsung), MotionSync-Bagless-Canister-Vacuum (Samsung), MotionSync-Canister-Superior-Accessories (Samsung), and Cleanwave-Sanitizing-Bagless-Vacuum (Verilux).

5.1.2. Data analysis

The data obtained from FIEM and Amazon reviews were unstructured text. To analyze these text data, Study 3 processed the data using a non-

hierarchical method, and words from the interview were only grouped based on their similarity of meaning, without classifying these grouped words in a hierarchical way. Study 3 compared the keywords of four components and investigated the common and distinct aspects of these components.

As shown in Figure 5.1, data analysis of Study 3 involved grouping words base on their similarity of meaning, extracting keywords from the results of FIEM and Amazon reviews, comparing the top keywords of FIEM and Amazon reviews, and identifying the first impression of the vacuum cleaner based on the common and distinct aspects of before-, during-, and after-use impressions of the product. The text data of FIEM and Amazon reviews were transformed into a list of words, using R software.

Non-hierarchical data processing and extracting keywords

Interview data are divided into separate words, each of which has a distinct meaning. They are grouped together according to their similarities, which refer to a similar meaning. This phase does not involve a task to produce the hierarchical structure of grouped words, but instead it resulted in a set of grouped words with the original meaning based on a non-hierarchical processing method, as mentioned in Section 4.1.

The frequency and the coverage rate were calculated for each word in order to extract keywords from a list of words. These values can serve as criteria for deciding the keywords. The frequency of words indicates the raw counts of words in a particular text. The coverage rate (% Cases) denotes the percentage of cases containing a particular word. In other words, the coverage rate is the percentage of participants who mentioned a particular word, thereby indicating the percentage of interviews where this word appears. Since 20 interviews were conducted in the data collection phase, the total number of cases of FIEM was 20. For the analysis of Amazon reviews, the total number of cases was 918.

Comparing the top-ranked keywords of FIEM and Amazon

Study 3 used the coverage rate for the purpose of determining the rankings of words. This study defined the top-ranked keywords as words with a high coverage rate. The top-ranked keywords of before-, during-, and after-use impressions were generated by determining the cut-off value of the coverage rate. The top keywords of Amazon reviews were also generated with the purpose of comparing these keywords with the top keywords of before-, during-, and after-use impressions obtained from FIEM. The comparison is focused mainly on investigating the similarity of keywords derived from FIEM and Amazon reviews. In other words, this comparison aimed to reveal the effectiveness of FIEM by demonstrating that most of the

keywords from Amazon reviews can found in the results obtained from FIEM.

To gain a comprehensive understanding of the results, keywords obtained from FIEM and Amazon reviews were also grouped into hedonic and pragmatic attributes. In Study 3, words relevant to product size or shape and feelings were classified as hedonic attributes. Words indicating function and part of the product were assigned into pragmatic attributes. Although this classification was carried out in consideration of the context of the words used, it may be somewhat subjective because it was based on a heuristic approach. The hedonic attribute was defined as 21 keywords: appearance, beautiful, children, color, design, excellent, family, health, large, nice, shape, simple, size, small, smooth, space, stable, storage, thin, unique, and visible. The pragmatic attribute was defined as 47 keywords: accessories, adjustment, attachment, bagless, body, broom, brush, burden, button, carpet, cord, detachable, dustbin, easy, empty, filter, floor, function, furniture, hair, handle, hard, head, heavy, hose, inconvenient, light, long, method, mode, move, noise, occupied, operation, pet, price, robot, separation, sofa, strong, suction, switching, troublesome, wand, washable, weight, and wheel. The percentage of keyword frequency was calculated to obtain the value of the hedonic and pragmatic attributes.

The percentage of keyword frequency was calculated to obtain the value of the hedonic and pragmatic attributes. The percentage of frequency means the ratio of the sum of keyword frequencies belong to the hedonic or pragmatic attributes to the total sum of keyword frequencies in a particular

component, such as the before-, during-, and after-use impressions, underlying frame, or reviews.

Deriving the common and distinct keywords of components

To define the first impression relevant to the product, it is important to understand the similarity and difference among before-, during-, and after-use impressions, in addition to identify the top ranked keywords of three impressions. The similarity among the impressions may demonstrate the general considerations regardless of the time span of experience. The difference among the impressions may be a key to explaining the unique considerations when building a particular impression towards the product. In this sense, Study 3 attempted to derive both the common and distinct keywords among the before-, during-, and after-use impressions.

The common keywords can be defined as the words that co-occur in the impressions. This can be considered as the general thoughts or feelings for the product. In this study, there may be two types of common keywords. One is the keywords common to three impressions (before, during, and after use). Another is the keywords common to two impressions (before and during use, before and after use, or during and after use).

The distinct keywords refer to the words that appear only in a certain impression. They were generated by removing the similarity from the list of top keywords for each impression. The similarity involves two

types of common keywords (mentioned above). Furthermore, Study 3 also tried to derive the distinct keywords based on tf-idf scores of keywords. The tf-idf score is popularly used in the field of text mining for the purpose of identifying keywords that appear frequently in a specific document, while they appear with a low frequency in other documents of the corpus (Matsuo & Ishizuka, 2004).

The tf-idf score is composed of term frequency (tf) and inverse document frequency (idf). The tf is used for measuring frequency of a word in the interview. The idf aims to measure frequency of words by reducing the impact of unimportant words. The tf-idf is defined by Equation 5.1.

$$\boldsymbol{TFIDF(w) = TF(w) * IDF(w)} \qquad \textbf{(5.1)}$$

where TF(w) denotes the number of times word w appears in a component of interviews divided by the total number of words that appeared in the interview for a component, and IDF(w) denotes log of the value generated by the total number of components composing the interview divided by the number of components with word w in them.

The results of common and distinct keywords were summarized as the rate of hedonic and pragmatic attributes by grouping common and distinct keywords into the hedonic and pragmatic attributes.

5.2. Results

5.2.1. Top keywords of FIEM and user reviews

Table 5.1 presents the results of top-ranked keywords of before-, during-, and after-use impressions, and the underlying frame obtained from FIEM. These keywords were selected by the coverage rate, more than 30%. For the during-use impression, the cut-off value was 70% with respect to the ranking of words. This is because participants tended to generate a lot of data for the actual use of the product, compared to other interview sections.

"Easy" and "dustbin" commonly emerged among the before-, during-, and after-use impressions, as well as the underlying frame. "Suction" was derived as the top-ranked keyword with a high frequency and coverage rate from interviews, which are relevant to the during- and after-use impressions and the underlying frame.

In the interview for before-use of the product, words related to the product size (e.g., storage, space, large, size, and stable) showed a high frequency and coverage rate. Keywords with more than 50% coverage rate were "color," "occupied," "storage," "wheel," "space," "size," "design," "large," "unique," "stable," and "shape." Words representing the parts of cleaners also emerged, such as "wheel," "dustbin," "body," "handle," and "head."

In the context of during-use, almost all keywords were associated with the usability of the product. The top-9 keywords appeared in all 20 interviews for the during-use impression. They were “carpet,” “smooth,” “accessories,” “button,” “separation,” “handle,” “body,” “suction,” and “easy.”

In the context of after-use, “light” and “noise” appeared as the important keywords based on the coverage rate, compared to other contexts. The top ranked keywords, which appeared in more than the half of the interviews, were as follows.

In the interview for the user’s underlying frame, “suction” was the most important word, with 100% coverage rate. Keywords with more than 50% coverage rate were “suction,” “washable,” “easy,” “large,” “family,” “children,” and “health.” It is interesting that “family,” “children,” and “health” were revealed as keywords that appeared in the half of the interviews. Participants also mentioned “beautiful” in the interview for the previous experience and the meaning or role of the product.

Table 5.1 The top keywords obtained from FIEM

Before-use Impression			During-use Impression			After-use Impression			Underlying Frame		
Term	**Freq.**	**% Cases**	**Term**	**Freq.**	**% Cases**	**Term**	**Freq.**	**% Cases**	**Term**	**Freq.**	**% Cases**
color	18	75%	**carpet**	75	100%	**easy**	18	85%	**suction**	33	100%
occupied	18	75%	**smooth**	49	100%	**light**	15	70%	**washable**	14	80%
storage	25	70%	**accessories**	106	100%	**handle**	22	70%	**easy**	15	65%
wheel	21	65%	**button**	75	100%	**accessories**	17	65%	**large**	13	60%
space	22	65%	**separation**	26	100%	**head**	17	65%	**family**	13	55%
size	17	60%	**handle**	96	100%	**noise**	14	55%	**children**	13	50%
design	19	55%	**body**	93	100%	**suction**	19	55%	**health**	12	50%
large	21	55%	**suction**	93	100%	**button**	17	50%	heavy	11	45%
unique	10	50%	**easy**	39	100%	**dustbin**	17	50%	inconvenient	9	45%
stable	13	50%	heavy	45	95%	**body**	12	50%	noise	14	40%
shape	11	50%	dustbin	113	95%	**space**	11	50%	broom	9	35%
heavy	11	45%	head	71	95%	detachable	9	45%	beautiful	10	30%
small	11	45%	storage	35	95%	hose	16	45%	bag	9	30%
dustbin	11	45%	cord	37	90%	adjustment	9	40%	space	7	30%
easy	9	45%	adjustment	31	90%	small	10	35%	strong	7	30%
simple	8	40%	light	26	85%	large	9	35%	function	6	30%
visible	7	35%	hose	33	85%	function	9	35%	troublesome	6	30%

body	9	35%	method	42	80%	washable	7	35%
handle	8	35%	sofa	35	80%	storage	9	35%
burden	11	30%	mode	32	80%	robot	9	30%
appearance	6	30%	operation	28	80%	weight	7	30%
head	11	30%	noise	29	80%	thin	6	30%
			strong	28	75%	strong	6	30%
			detachable	17	75%			
			switching	16	70%			
			wheel	20	70%			

Table 5.2 The top keywords obtained from Amazon reviews

Term	Freq.	# Cases	% Cases
floor	883	643	70%
easy	867	634	69%
pet	716	584	64%
suction	716	534	58%
carpet	1015	519	57%
brush	636	388	42%
attachment	485	375	41%
space	398	358	39%
head	540	355	39%
light	429	341	37%
hair	423	272	30%
empty	316	269	29%
small	337	268	29%
long	274	244	27%
cord	328	242	26%
handle	282	218	24%
hard	281	218	24%
dustbin	239	189	21%
hose	261	187	20%
price	206	172	19%
filter	213	157	17%
button	173	146	16%
storage	161	143	16%
furniture	168	138	15%
wand	176	136	15%
large	130	126	14%
nice	138	123	13%
move	131	115	13%
excellent	120	114	12%
bagless	139	113	12%
heavy	126	112	12%

Table 5.2 lists the top-ranked keywords of Amazon reviews, based on the percentage of cases where a particular word appears. These keywords were selected by the coverage rate, more than 12%. "Floor," "easy," "pet," "suction," and "carpet" were the most important keywords, mentioned in the reviews of more than 50%. According to the occurrence ratio of words, the priorities of product attributes were as follows: brush, head, cord, handle, dustbin, hose, filter, and button. Words related to the weight and size of the product, were also revealed as the important keywords, such as "light," "small," "storage," and "large." "Design" was mentioned in 11% of the reviews.

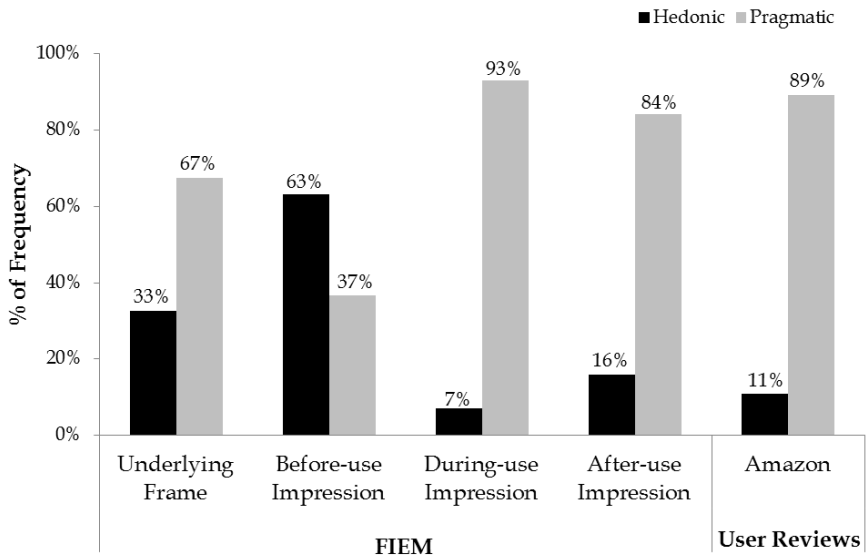


Figure 5.2 Hedonic and pragmatic rates of the keywords obtained from FIEM and user reviews

As shown in Figure 5.2, the keywords obtained from Amazon reviews showed a similar tendency to those of the keywords of during- and after-use impressions. While the rate of the pragmatic attributes in Amazon reviews, and during- and after-use impressions was definitely higher than of the hedonic attribute, keywords of the before-use impression were more related to the hedonic attribute, rather than those of the pragmatic attribute.

In the context of before use, the rate of the hedonic attribute was 63 %, while that of the pragmatic attribute was 37%. In the underlying frame, the rate of the hedonic attribute was 33%, which is higher compared to the results of during- and after-use impressions and Amazon reviews.

5.2.2. Common keywords of before-, during-, and after-use impressions

Table 5.3 presents a summary of keywords based on the common characteristics among each impression for the product. Regardless of the point of use, “body,” “dustbin,” “easy,” “handle,” “head,” and “storage” served as the critical keywords that can show the similarities among the before-, during-, and after-use impressions.

Table 5.3 Common keywords among before-, during-, and after-use impressions

		Before-use Impression		During-use Impression		After-use Impression	
Context	**Term**	**Freq.**	**% Cases**	**Freq.**	**% Cases**	**Freq.**	**%Cases**
Before, during, and after use	body	9	35%	93	100%	12	50%
	dustbin	11	45%	113	95%	17	50%
	easy	9	45%	39	100%	18	85%
	handle	8	35%	96	100%	22	70%
	head	11	30%	71	95%	17	65%
	storage	25	70%	35	95%	9	35%
Before and during use	heavy	11	45%	45	95%	-	-
	wheel	21	65%	20	70%	-	-
Before and after use	large	21	55%	-	-	9	35%
	small	11	45%	-	-	10	35%
	space	22	65%	-	-	11	50%
During and after use	accessories	-	-	106	100%	17	65%
	adjustment	-	-	31	90%	9	40%
	button	-	-	75	100%	17	50%
	detachable	-	-	17	75%	9	45%
	hose	-	-	33	85%	16	45%
	light	-	-	26	85%	15	70%
	noise	-	-	29	80%	14	55%
	strong	-	-	28	75%	6	30%
	suction	--	--	93	100%	19	55%

The before- and during-use impressions had a common relation to "heavy" and "wheel," which are associated with weight issues. In both before- and after-use impressions, "large," "small," and "space" appeared as the important keywords that can show their similarities. "Large" and "small" refer to the size and volume of a product.

On the other hand, it was revealed that the common keywords between during- and after-use impressions tend to focus more on the basic functional aspects of the product and the product attributes, compared to other common keywords. Considering the during- and after-use impressions, the common keywords were "accessories," "adjustment," "button," "detachable," "hose," "light," "noise," "strong," and "suction."

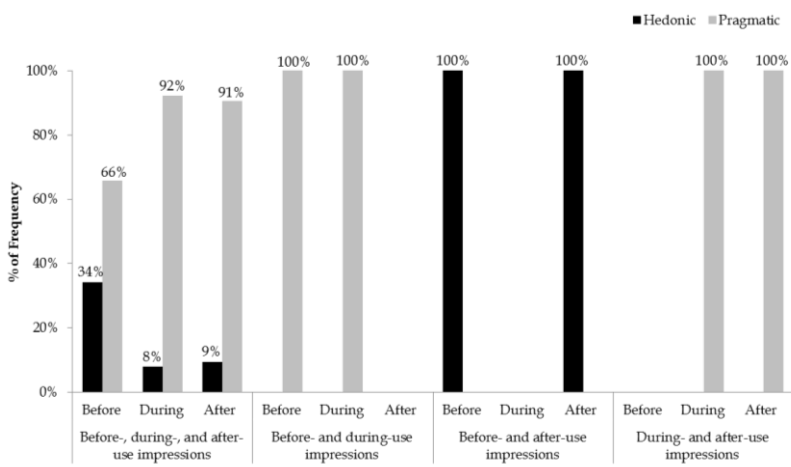


Figure 5.3 Hedonic and pragmatic rates of the common keywords

As shown in Figure 5.3, the common keywords among before-, during-, and after-use impressions had a relatively strong relation with the pragmatic attribute. Of these keywords, 66% emerged from the before-use impression were relevant to the pragmatic attribute. More than 90% of these keywords that emerged from during- and after-use impressions could be explained by the pragmatic attribute.

Figure 5.3 also shows a perfect association between the pragmatic attribute and keywords that commonly occur in before- and during-use impressions, as well as in during- and after-use impressions. Contrary to this tendency, there was an entire relation between the hedonic attribute and keywords that commonly occur in before- and after-use impressions.

5.2.3. Distinct keywords of before-, during-, and after-use impressions

Table 5.4 presents a summary of keywords based on the distinct characteristics across impressions for the product. The distinct keywords of the before-use impression were "color," "appearance," "burden," "design," "occupied," "shape," "simple," "size," "stable," "unique," and "visible."

In the before-use impressions, "color," "occupied," and "size" were revealed as unique keywords observed in more than 60% of the interviews. However, "burden" and "visible" acted as discriminators, despite the relatively low coverage rate.

Table 5.4 Distinct keywords of the before-, during-, and after-use impressions

Context	Term	Freq.	% Cases
Before use	color	18	75%
	appearance	6	30%
	burden	11	30%
	design	19	55%
	occupied	18	75%
	shape	11	50%
	simple	8	40%
	size	17	60%
	stable	13	50%
	unique	10	50%
	visible	7	35%
During use	carpet	75	100%
	smooth	49	100%
	cord	37	90%
	method	42	80%
	mode	32	80%
	operation	28	80%
	sofa	35	80%
	separation	26	100%
	switching	16	70%
After use	function	9	35%
	robot	9	30%
	thin	6	30%
	washable	7	35%
	weight	7	30%

In the before-use impressions, “color,” “occupied,” and “size” were revealed as unique keywords observed in more than 60% of the interviews. However, “burden” and “visible” acted as discriminators, despite the relatively low coverage rate.

For the during-use impression, the distinct keywords were “carpet,” “smooth,” “cord,” “method,” “mode,” “operation,” “sofa,” “separation,” and “switching.” These words were focused on the movement and management of the product parts, especially cord. “Carpet,” “sofa,” and “separation” appeared in all 20 interviews. The distinct keywords emerging after use of the product were focused on “function,” “robot,” “thin,” “washable,” and “weight.” The rate of participants who mentioned these words ranged from 30% to 35%.

Table 5.5 represents the top-10 keywords of the before-, during-, and after-use impressions based on tf-idf scores. For the before-use impression, keywords with the highest tf-idf scores were “design,” “color,” “burden,” “unique,” “simple,” “wheel,” “large,” ,”visible,” “occupied,” and “appearance.” These results in Table 5.5 were consistent with the keywords of the before-use impression in Table 5.4. As with the results in Table 5.4, these keywords highlighted the product appearance, including the overall design aspects and the shape or volume of the product. Among these words, “wheel,” which appeared in 65 % of interview cases was the only word related to the product attribute. This means that 13 participants mentioned “wheel” in the interviews as the before-use impression.

Table 5.5 Distinct keywords of the before-, during-, and after-use impressions based on tf-idf scores

Context	Term	Freq.	% Cases	TF-IDF
Before use	design	19	55%	0.773
	color	18	75%	0.732
	burden	11	30%	0.448
	unique	10	50%	0.407
	simple	8	40%	0.326
	wheel	21	65%	0.315
	large	21	55%	0.315
	visible	7	35%	0.285
	occupied	18	75%	0.270
	appearance	6	30%	0.244
During use	carpet	75	100%	1.030
	smooth	49	100%	0.673
	method	42	80%	0.577
	accessories	106	100%	0.537
	press	38	65%	0.522
	cord	37	90%	0.508
	sofa	35	80%	0.481
	mode	32	80%	0.439
	operation	28	80%	0.385
	button	75	100%	0.380
After use	robot	9	30%	0.353
	accessories	17	65%	0.246
	button	17	50%	0.246
	light	15	70%	0.217
	noise	14	55%	0.203
	small	10	35%	0.145
	detachable	9	45%	0.130
	adjustment	9	40%	0.130
	large	9	35%	0.130
	function	9	35%	0.130

In Table 5.5, keywords of the during-use impression were "carpet," "smooth," "method," "accessories," "press," "cord," "sofa," "mode," "operation," and "button." Among these words, "carpet" showed the highest tf-idf scores and appeared in all interviews. Although, "button" appeared in all interviews with the highest raw counts, their tf-idf scores were relatively low compared to "carpet," "smooth," or "accessories." "Operation" was ranked lower in spite of the high occurrence in cases.

In Table 5.5, keywords of the after-use impression were "robot," "force," "accessories," "button," "light," "noise," "power," "small," "detachable," and "adjustment." Among these words, "robot" showed the highest tf-idf scores and appeared in 30% of interviews. During the interview for the after-use impression, keywords that frequently appeared in interviews tended to have a high tf-idf score.

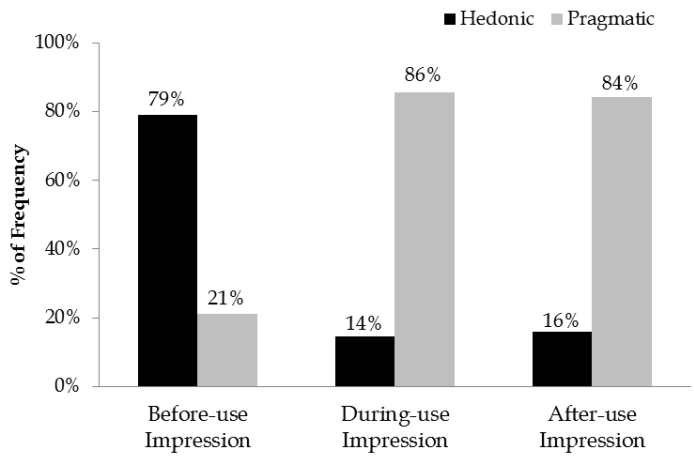


Figure 5.4 Hedonic and pragmatic rates of the distinct keywords

As shown in Figure 5.4, the distinct keywords of the before-use impression can be explained 79% by the hedonic attribute and 21% by the pragmatic attribute. However, it was revealed that the pragmatic attribute explains more than 80% of the keywords, representing the distinctive aspect of during- and after-use impressions.

5.3. Discussion

The results obtained from Amazon reviews showed similar characteristics with the keywords of during- and after-use impressions. These keywords tended to be classified into the pragmatic attribute, compared to the keywords in the before-use impression and the underlying frame. In addition to this fact, most of keywords appeared in Amazon reviews also emerged in the list of keywords of during- and after-use impressions. This is due to the fact that Amazon reviews emerge after the product has been used. This implies that FIEM has a general ability to identify the impression for the product, despite smaller size of data than the analysis of web reviews.

The similarities of before-, during-, and after-use of the products can be identified based on the analysis of top-ranked words and common words among them, by comparing each word from the contexts. In terms of their similarities, “easy” and “dustbin” were the main interests of users for

the evaluation of cleaners. “Body,” “dustbin,” “handle,” “head,” and “storage” were also revealed as the common needs for the cleaner, based on their ranks and co-occurrences. Besides, keywords from the underlying frame evaluation showed a higher relation with the hedonic attribute, compared to the keywords of during- and after-use impressions. This implies that user’s previous experience with the product type can play a significant role in the formation of first impression of the newly exposed product.

Compared to the common needs in before and after use of the product, users paid more attention to the product shape and size when they just see the product without direct interaction. Especially, it turned out that users tend to focus on the size and space of the product in a relation with the before-use context (i.e., the first impression). The study revealed a tendency to focus on the visual aspects of the product, under the relationship between before- and after-use of the product.

As expected, the difference of before-use experience was more concentrated on the visual aspects of the product, compared to during- and after-use of the product. In this sense, the distinct keywords with regard to before-use situations were defined as “color,” “appearance,” “burden,” “design,” “occupied,” “shape,” “simple,” “size,” “stable,” “unique,” and “visible.” This result was similar to that of the important keywords based on tf-idf scores. Aligned with many studies (Berkowitz, 1987; Creusen & Schoormans, 2005; Norman, 1988), the impression formed before use also

had a functional characteristic, such as burden, as well as several hedonic characteristics.

Study 3 tried to attempt to analyze users' thoughts or attitudes toward the products from multiple perspectives, with the purpose of providing both general and unique understanding for the first impressions that users have in mind for a product. In this sense, this study provided a practical and simple way to define the important keywords in user interviews based on the similarity and difference among the interview components. This was done based on three perspectives: words with a high frequency and their raw ranking, words providing a general description, and words explaining a unique characteristic of impressions generated by a product. Despite these implications, this study has a limitation of investigating only a functional product. The main focus of a functional product is performance, rather than the physical attribute or services (Markeset & Kumar, 2005Markeset & Kumar, 2005). In this sense, keywords of the during-use impression were overwhelmingly associated with the pragmatic attributes.

5.4. Summary

The results described in Section 5.2 showed a general ability of FIEM to ascertain the similarities and differences between before-use of the product

and other contexts of use. Based on keyword comparison strategies presented in Section 4.2, researchers may extract and understand the critical information relevant to the before-use contexts, which can be called the first impression, from multiple perspectives. FIEM can be served as a practical tool to identify the core needs for the first impression in terms of the similarities and differences between during-use and after-use situations.

Chapter 6.
DISCUSSION AND CONCLUSION

6.1. Summary of research findings

The primary aim of this dissertation was to design a framework for understanding of first impressions of products, while focusing on the temporal and hedonic aspects of experience that are generated by interacting with a product. For this purpose, the dissertation identified the characteristics of first impression relevant to a product in a relation with time spans and hedonic qualities of user experience. The main assumptions for constructing the framework were derived based on a literature review on consumer choice, impression formation, and hedonic aspects of user experience and its dynamics. The dissertation also revealed that first impressions are derived from ever-changing experience, and thus it should be understood through a close relationship with during- and after-use of contexts and previous experiences of the product type.

To collect meaningful information on the first impression of the product, this dissertation aimed to perform a study using the interview data in a systematic way. To address these requirements, two major

challenges for employing the unstructured data were identified. The first problem was using hierarchical categorization for creating the logical structure in order to understand the user experience. Another problem was the lack of practical approaches to extract insights from the unstructured data for the purpose of capturing users' thoughts and feelings toward the product, not of developing a strict algorithm for extracting keywords from the data.

According to these findings, the dissertation developed a conceptual framework based on the cumulative and continuous characteristics of first impressions of products. It also developed a set of interview questions that help to collect the data on first impressions, in stages. In addition to the data collection method, two main considerations for the interview data were presented in order to solve the abovementioned challenges in the field of user experience.

Study 1 (see Section 4.1) aimed to identify the need to apply a non-hierarchical processing method to preserve the diversity and originality of users' responses, by comparing the hierarchical and non-hierarchical categorization of the interview data. Based on the results of Study 1, Study 2 (see Section 4.2) was designed to develop a simple and practical approach to capture simultaneously the common needs or thoughts for the product and the hidden, implicit needs. These two studies provided the empirical evidence for analyzing the interview data for the purpose of understanding user experience of the product. They can be characterized, collectively, as an approach to extract the crucial information relevant to user experience

for the product, which aims to derive the representative and discriminate keywords without building a hierarchical structure of data.

Based on these studies and the literature review, this dissertation suggested an interview method (FIEM) to help to investigate first impression of products based on the notion of experiential capital. To describe the validity of FIEM, Study 3 (see Chapter 5) was conducted to identify the first impression of cleaners, based on the purposed method. Study 3 compared the top-ranked keywords derived from FIEM and Amazon reviews in order to demonstrate the generalizability of FIEM. Study 3 characterized the first impression relevant to the cleaners by deriving the common and distinct keywords among the before-, during-, and after-use impressions. The results provided a comprehensive consensus with previous studies on the first impressions of products, ensuring the usefulness of FIEM.

6.2. Implications and limitations

This dissertation showed several practical and academic implications. Although FIEM was developed for the purpose of identifying the first impression related to the product, its temporal aspects make it useful for understanding the general aspects of user experience, as well as the distinctive characteristics of first impressions and their relationships with

the products. Most of all, FIEM is a new attempt to explain the user experience components, focusing on continuous time spans, both from the macro and micro perspectives. It can also provide a systemic method to researchers who are willing to employ unstructured data for investigating the user experience, from data collection to analysis.

In addition to these implications, it will help designers to build concepts that can accomplish the goals of the company and achieve the intended impression, by providing a basis for their decisions. The FIEM can also serve as a research tool to gain an overall perception on a particular product, as well as ascertain users' real desire for the products. In this sense, applying FIEM might provide more insight into the consumers' behaviour and their values.

However, despite its practical implications, this dissertation was limited because it applied the proposed method to a particular type of the product (i.e., a functional product). Thus, further research on diverse product types is needed to utilize the FIEM effectively.

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APPENDICES

Appendix A. Results of attributes, consequences, and values in Study 1

Appendix B. Data-structuring process in Study 1

Appendix C. Network of user groups in Study 1

Appendix D. Questionnaire in Study 2

Appendix E. Interview template in Study 3

Appendix A: Results of attributes, consequences, and values in Study 1

Attributes	Consequences	Values
casual chat	advancement in games	accomplishment
club activities	appearance management	comfortable life
cosmetics contents	attractiveness	freedom
cosmetics surgery review	beauty	fun and entertainment
diet tips	build sympathy	self-esteem
fashion contents	challenge	self-fulfillment
game	competitive advantage	warm relationships
game character	convenient	wisdom
game control	creativity	
game news	cute	
game quest	diverse experience	
game ranking	easy	
game story	economic benefit	
humor	enculturation	
information search	envy	
movie	excitement	
music	finding a trendy style	
news	gaining confidence	
online shopping	getting conversation topics	
personal homepage	individuality	
photo	making new friends	
soap opera	managing social networking activities	
star gossip	obtaining information	
star news	peer culture	
star photo	popularity	
star video	saving time	
stock market news	self-satisfaction	
user comments	solving problems	
user group	sound mind	
webcomic	stress relief	
	time killing	
	vicarious experience	
	vicarious satisfaction	

Appendix B: Data-structuring process in Study 1

Example of data structuring based on the hierarchical method

Step 1: Grouping words with similar meanings

Example of grouping words

Term	Similar term
challenging spirit	challenge, dream, purpose, inducing behavior, a desire for victory, strong character
accomplishment	accomplishment, the joy of success
creating a competitive advantage	competition, win, prestige, better item, win or lose, good item, high status, competitive entrance exam
reality	world, reality, truth
confidence	confidence
popularity	popular, popularity
self-satisfaction	self-satisfaction, satisfaction

Step 2: Labeling each word with the attributes, consequences, and values

Example of attributes, consequences, and values resulted from the hierarchical method

Attributes	Consequences	Values
game character	making new friends	accomplishment
game quest	getting conversation topics	fun and entertainment
star photo	enculturation	warm relationships
club activities	easy	comfortable life
user comments	excitement	self-fulfillment
online shopping	build sympathy	
web comic	peer culture	
movie	vicarious experience	
	vicarious satisfaction	
	competitive advantage	
	time killing	

Step 3: Generating the relation matrix based on the relation frequency between attributes, consequences, and values

Example of the relation matrix obtained from the hierarchical method

		Consequences										Values		
		Competitive advantage	Individuality	Stress Relief	Beauty	Popularity	Convenient	Self- satisfaction	Sound mind	Attractiveness	Envy	Fun and entertainment	Warm relationships	comfortable life
Attributes	**Casual chat**	2	2	4	0	1	0	0	2	2	4	0	0	0
	News	0	0	2	0	0	2	0	0	0	2	0	0	0
	Personal homepage	4	0	3	0	1	0	0	4	0	3	0	0	0
	Fashion contents	4	6	0	7	4	0	1	4	6	0	0	0	0
	Diet tips	4	3	1	9	3	0	2	4	3	1	0	0	0
	Cosmetics contents	5	3	0	9	3	2	0	5	3	0	0	0	0
	Cosmetics surgery review	0	1	0	1	0	0	0	0	1	0	0	0	0
	Humor	1	0	1	0	1	0	0	1	0	1	0	0	0
Consequences	**Making new friends**	2	0	2	0	0	0	0	0	0	0	3	13	2
	Managing social networking activities	3	1	7	0	5	0	0	0	0	0	4	36	12
	Enculturation	0	0	0	0	0	0	0	0	0	0	4	8	0
	Easy	0	0	2	0	0	3	0	0	0	0	1	0	3

Example of data structuring based on the non- hierarchical method

Step 1: Grouping words with similar meanings

Example of grouping words

Term	Similar term
challenging spirit	challenge, dream, purpose, inducing behavior, a desire for victory, strong character
accomplishment	accomplishment, the joy of success
creating a competitive advantage	competition, win, prestige, better item, win or lose, good item, high status, competitive entrance exam
reality	world, reality, truth
confidence	confidence
popularity	popular, popularity
self-satisfaction	self-satisfaction, satisfaction

Step 2: Generating the relation matrix based on the relation frequency between each word

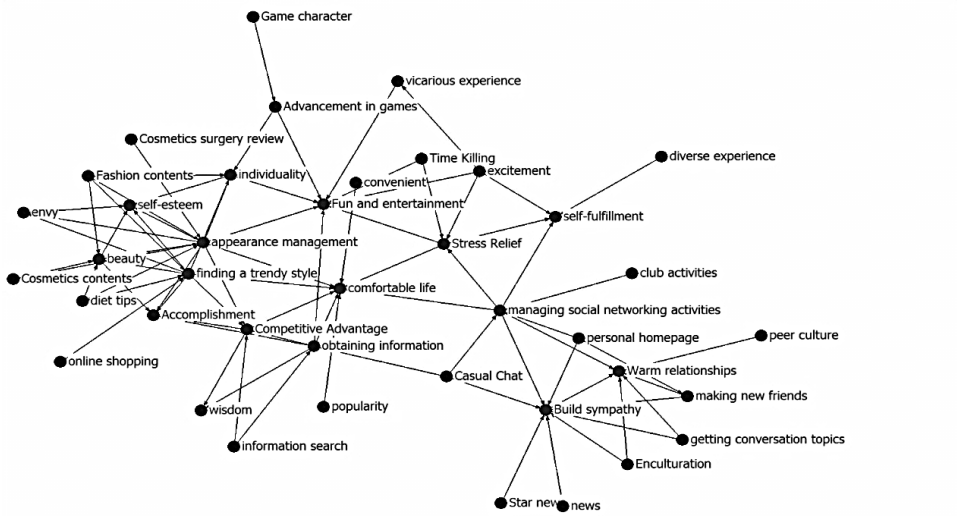
Example of the relation matrix obtained from the non-hierarchical method

	Diverse experience	Vicarious satisfaction	Cosmetic surgery review	Appearance management	Image management	Diet tips	Skin care tips	Make-up tips	Cosmetics	Improving one's fashion style
Appearance management	0	0	0	0	0	0	0	0	0	16
Diet tips	0	0	0	10	0	0	0	0	0	0
Skincare tips	0	0	0	11	0	0	0	0	0	0
Make-up tips	0	0	0	12	3	0	0	0	0	0
Cosmetics	0	0	0	2	0	0	0	0	0	0
Improving one's fashion style	0	0	0	0	8	0	0	0	0	0
Fashion contents	0	0	0	8	0	0	0	0	0	10
Online shopping	0	0	0	0	0	0	0	0	0	1

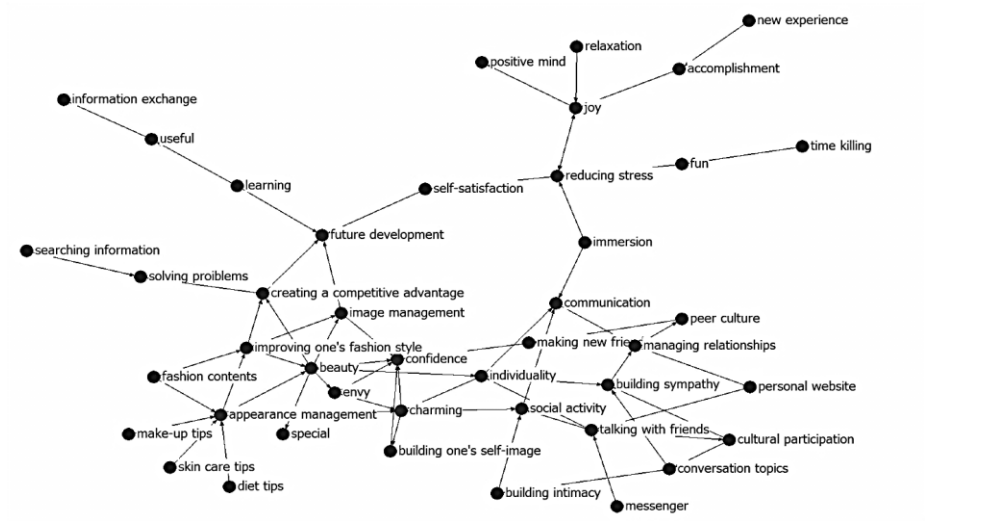
Appendix C: Network of user groups in Study 1

Network of the entire user group: cutoff value=5

Hierarchical data analysis

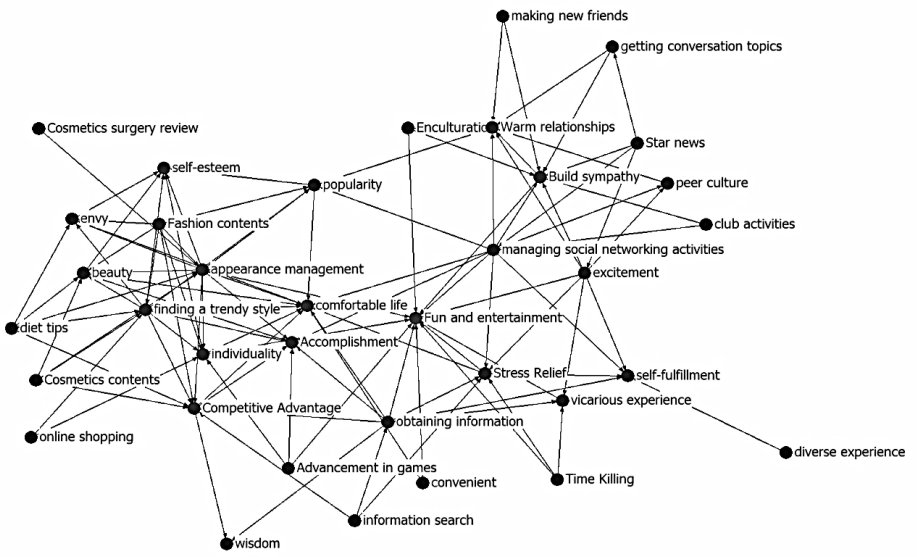


Non-hierarchical data analysis

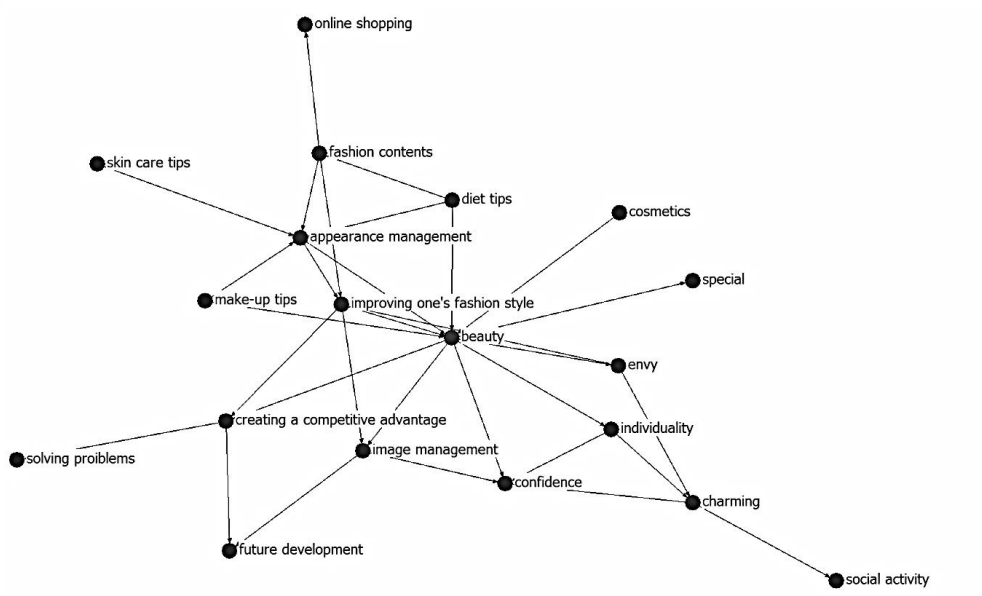


Network of fashion group: cutoff value=3

Hierarchical data analysis

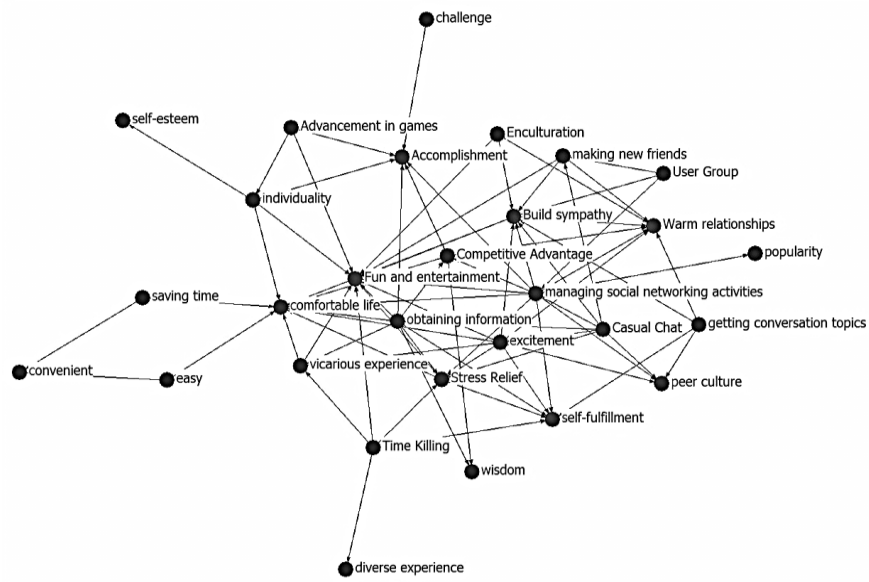


Non-hierarchical data analysis



Network of game group: cutoff value=2

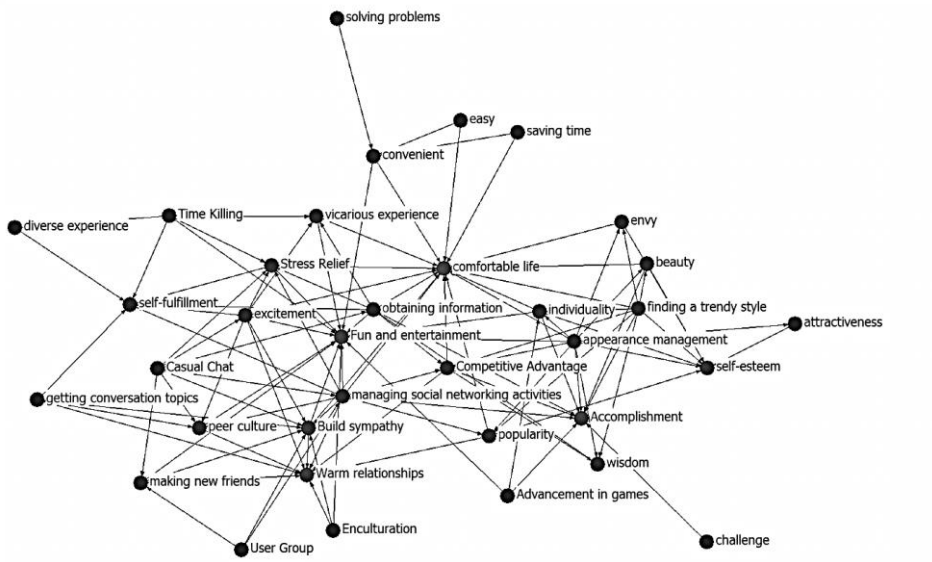
Hierarchical data analysis



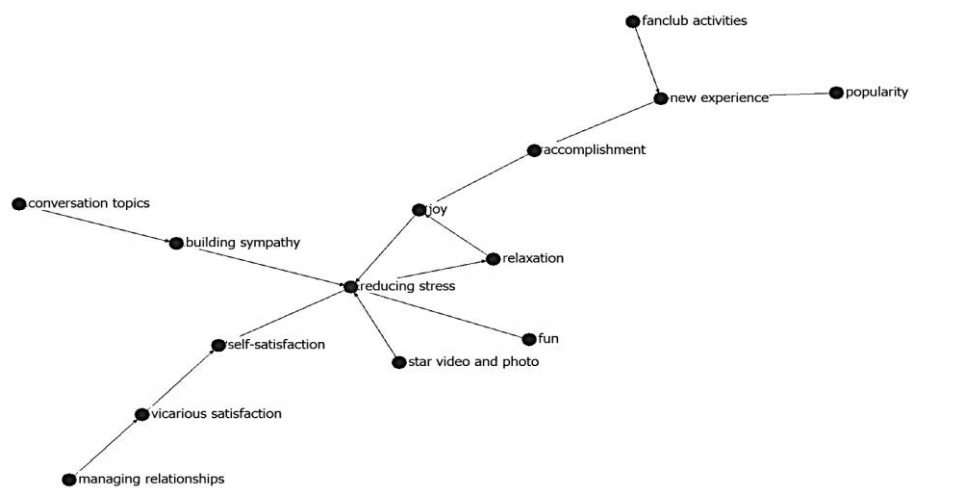
Non-hierarchical data analysis

Network of celebrity group: cutoff value=2

Hierarchical data analysis



Non-hierarchical data analysis



Appendix D: Questionnaire in Study 2

[Korean version]

2013 카메라 셔터음 감성평가

본 설문 평가에 참여해 주셔서 대단히 감사합니다. **서울대학교 HIS연구실에서는** 카메라 셔터음에 대한 감성평가를 진행하고 있습니다. 모든 질문은 주관식이며, 들리는 소리에 대한 느낌과 가장 적합하다고 생각되는 곳에 표시를 해주시면 됩니다. 본 조사 질문의 응답내용은 통계법 제8조에 의거하여 제품의 개선 및 개발의 목적으로만 사용됩니다.

기본 인적 사항

1. 귀하의 성함을 기입하십시오. _____
2. 귀하의 성별을 선택하십시오. ① 남자 ② 여자
3. 귀하의 나이를 기입하십시오. 만_____세
4. 귀하의 카메라 사용경력을 기입하십시오(동아리 활동 경력) _____

평가 실험 시작

이제부터 평가 실험이 시작됩니다. 총 10개의 카메라 셔터음을 차례대로 들으시고 각각의 셔터음에 대한 주관적 느낌을 해당란에 표기해주시면 됩니다.

1. 카메라 셔터음이 얼마나 깔끔한 느낌을 준다고 생각하십니까?

①	②	③	④	⑤	⑥	⑦
전혀 깔끔하지 않다			보통이다			매우 깔끔하다

2. 카메라 셔터음이 얼마나 딱딱한 느낌을 준다고 생각하십니까?

①	②	③	④	⑤	⑥	⑦
전혀 딱딱하지 않다			보통이다			매우 딱딱하다

3. 카메라 셔터음이 얼마나 고전적인 느낌을 준다고 생각하십니까?

①	②	③	④	⑤	⑥	⑦
전혀 고전적이지 않다			보통이다			매우 고전적이다

4. 카메라 셔터음이 얼마나 기계적인 느낌을 준다고 생각하십니까?

①	②	③	④	⑤	⑥	⑦
전혀 기계적이지 않다			보통이다			매우 기계적이다

5. 카메라 셔터음이 얼마나 난잡한 느낌을 준다고 생각하십니까?

①	②	③	④	⑤	⑥	⑦
전혀 난잡하지 않다			보통이다			매우 난잡하다

6. 카메라 셔터음이 얼마나 둔탁한 느낌을 준다고 생각하십니까?

①	②	③	④	⑤	⑥	⑦
전혀 둔탁하지 않다			보통이다			매우 둔탁하다

7. 카메라 셔터음이 얼마나 재미있는 느낌을 준다고 생각하십니까?

① 전혀 재미있지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 재미있다

8. 카메라 셔터음이 얼마나 깊은 느낌을 준다고 생각하십니까?

① 전혀 깊지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 깊다

9. 카메라 셔터음이 얼마나 맑은 느낌을 준다고 생각하십니까?

① 전혀 맑지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 맑다

10. 카메라 셔터음이 얼마나 모던한 느낌을 준다고 생각하십니까?

① 전혀 모던하지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 모던하다

11. 카메라 셔터음이 얼마나 복잡한 느낌을 준다고 생각하십니까?

① 전혀 복잡하지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 복잡하다

12. 카메라 셔터음이 얼마나 부드러운 느낌을 준다고 생각하십니까?

① 전혀 부드럽지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 부드럽다

13. 카메라 셔터음이 얼마나 상쾌한 느낌을 준다고 생각하십니까?

① 전혀 상쾌하지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 상쾌하다

14. 카메라 셔터음이 얼마나 세련된 느낌을 준다고 생각하십니까?

① 전혀 세련되지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 세련되다

15. 카메라 셔터음이 얼마나 시끄러운 느낌을 준다고 생각하십니까?

① 전혀 시끄럽지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 시끄럽다

16. 카메라 셔터음이 얼마나 짜증스런 느낌을 준다고 생각하십니까?

① 전혀 짜증스럽지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 짜증스럽다

17. 카메라 셔터음이 얼마나 편안한 느낌을 준다고 생각하십니까?

① 전혀 편안하지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 편안하다

18. 카메라 셔터음이 얼마나 단아하고 정숙한 느낌을 준다고 생각하십니까?

① 전혀 단아하거나 정숙하지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 단아하고 정숙하다

19. 카메라 셔터음이 얼마나 울림 있는 느낌을 준다고 생각하십니까?

① 전혀 울리지 않는다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 울린다

20. 카메라 셔터음이 얼마나 불안정한 느낌을 준다고 생각하십니까?

① 전혀 불안정하지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 불안정하다

21. 카메라 셔터음이 얼마나 가벼운 느낌을 준다고 생각하십니까?

① 전혀 가볍지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 가볍다

22. 카메라 셔터음이 얼마나 텅 빈듯한 느낌을 준다고 생각하십니까?

① 전혀 텅빈듯한 느낌을 주지 않는다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 텅 빈듯한 느낌이 난다

23. 카메라 셔터음이 얼마나 강한 느낌을 준다고 생각하십니까?

① 전혀 강하지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 강하다

24. 카메라 셔터음이 얼마나 여운이 있다고 생각하십니까?

① 전혀 여운이 남지 않는다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 여운이 남는다

25. 카메라 셔터음이 얼마나 무거운 느낌을 준다고 생각하십니까?

① 전혀 무겁지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 무겁다

26. 카메라 셔터음이 얼마나 명확한 느낌을 준다고 생각하십니까?

① 전혀 명확하지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 명확하다

27. 카메라 셔터음이 얼마나 거친 느낌을 준다고 생각하십니까?

① 전혀 거칠지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 거칠다

28. 카메라 셔터음이 얼마나 균형 있는 느낌을 준다고 생각하십니까?

① 전혀 균형 있지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 균형 있다

29. 카메라 셔터음이 얼마나 조용한 느낌을 준다고 생각하십니까?

① 전혀 조용하지 않다 ② ③ ④ 보통이다 ⑤ ⑥ ⑦ 매우 조용하다

30. 카메라 셔터음이 얼마나 스마트하다고 생각하십니까?

_____(/100점)

31. 카메라 셔터음이 얼마나 인간적이라고 생각하십니까?

_____(/100점)

32. 카메라 셔터음에 대해 전체적으로 얼마나 만족하십니까?

_____(/100점)

[English version]

Survey

Name:
Gender:
Age:
Years of experience:

Please mark your feelings with the shutter sound.

	strongly disagree			neutral			strongly agree
	1	2	3	4	5	6	7
clean							
hard							
classical							
metallic							
messy							
dull							
funny							
deep							
pure							
modern							
complicated							
soft							
fresh							
refined							
noisy							
annoying							
comportable							
noble							
resonating							
unstable							
light							
hollow							
strong							
lingering							
heavy							
clear							
harsh							
balanced							
silent							

Survey

Do you feel this sound is smart? _____ (/100)

Do you feel this sound is friendly? _____ (/100)

Do you feel this sound is satisfactory? _____ (/100)

Appendix E: Interview template in Study 3

[Korean version]

청소기 사용 경험에 대한 인터뷰

본 인터뷰에 참여해 주셔서 대단히 감사합니다. **서울대학교 HIS연구실에서는** 청소기 에 대한 평가를 진행하고 있습니다. 평소 청소기 사용 경험에 기반하여 제시되는 질문에 대해 솔직하게 답변해주시기 바랍니다. 본 조사 질문의 응답내용은 통계법 제8조에 의거하여 제품의 개선 및 개발의 목적으로만 사용됩니다.

기본 사항

1. 귀하의 성함을 기입하십시오. _____

2. 귀하의 나이를 기입하십시오(만 나이). _____세

3. 귀하는 하루에 청소기를 몇 번 사용하며, 한 번 사용 시 평균 소요 시간을 적어주십시오.

_____

4. 귀하가 현재 보유하신 청소기의 종류를 기입하십시오.

_____

청소기 사용 경험에 대한 인터뷰

매장이라고 가정하고 5분 동안 청소기들을 살펴본 뒤 질문에 답해주십시오.

1. 청소기를 보고 드는 생각을 자유롭게 말해주십시오.

청소기 사용 경험에 대한 인터뷰

다음의 질문에 자유롭게 답해주십시오.

3. 현재 보유하고 있는 청소기의 장점 및 단점을 자유롭게 말해 주십시오.

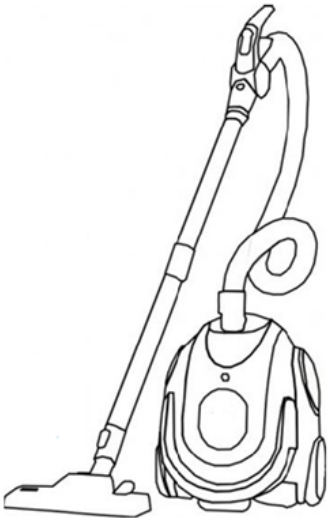
4. 청소의 의미와 청소기의 역할이 무엇이라 생각하는지 자유롭게 말해 주십시오.

5. 청소를 하면서 기억에 남았던 일화에 대해서 자유롭게 말해 주십시오.

청소기 사용 경험에 대한 인터뷰

다음의 질문에 자유롭게 답해주십시오.

6. 기술적으로 불가능한 부분이 없을 때, 다음의 청소기 그림에서 개선하고 싶은 부분에 동그라미를 그리고 선택하신 부분에 대하여 어떠한 점을 개선하고 싶은지 자유롭게 써주십시오.



청소기 사용 경험에 대한 인터뷰

다음의 질문에 자유롭게 답해주십시오.

7. 청소기를 지인에게 선물한다면 어떤 사항을 중요하게 고려할지 자유롭게 말해주십시오.

[English version]

Interview

Name:
Age:
Frequency and duration of use (/day):
Model:

1. Please describe your feelings or thoughts when you first saw this product in the consideration of product appearance.

_____

_____

2. Please tell us whatever you think during the use of the product.

_____

_____

3. Please describe the advantages and disadvantages of your product you currently have.

_____

_____

4. Please describe the role and meaning of the product you have in mind.

_____

_____

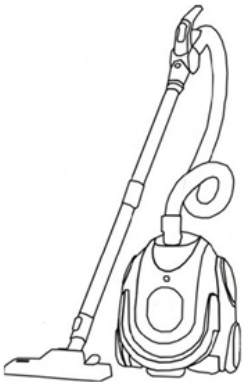
5. Please describe your memorable anecdotes related to the product.

_____

_____

Interview

6. Please point out the parts to be improved in the picture and write down your idea with a simple sketch (Assuming that everything is technically possible).



7. Please describe what is important to give this product to your friends as a gift.

국문초록

본 논문의 목적은 사용자 경험의 역동성을 고려하여 제품의 첫인상을 파악할 수 있는 인터뷰 방법을 설계하고 그것을 실제 사례에 적용시켜보는 것이다. 이를 위해 이 논문은 사용자 경험과 제품의 첫인상에 관련된 문헌조사를 바탕으로 첫인상을 경험의 축적이라는 측면에서 이해할 수 있는 프레임워크를 제시하였다. 이 프레임 워크는 제품을 사용하기 전, 사용 중, 사용 후에 발생하는 경험과 사용자가 제품에 대해 기존에 보유하고 있던 경험이 서로 연결될 수 있으며, 이것이 다시 새로운 제품의 첫인상을 규정하는데 영향을 준다고 가정하였다.

이 논문은 위의 프레임워크를 기반으로 "FIEM: the First Impression Elicitation Method" 이라는 인터뷰 방법을 제안하였다. FIEM 은 5 단계로 이루어진다. 첫째, 인터뷰에 사용할 제품을 선정하고 인터뷰 참여자 모집한다. 둘째, 제품을 직접적으로 사용하기 전에 제품의 인상을 평가한다. 셋째, 제품을 사용하는 중에 제품에 대한 인상을 평가한다. 넷째, 평가 시작 전에 제품에 대해 가지고 있던 인상을 평가한다. 마지막으로, 제품을 사용한 후에 제품에 대한 인상을 평가한다.

이 방법을 실제 사례에 적용해 보기 전에, 사용자 경험 연구 분야에서 인터뷰 자료 분석 시 발생하는 주요 이슈를 해결하기 위해 두 가지 연구가 수행되었다 첫 번째 연구 (N=17) 는 인터뷰 자료에서 사용자 그룹의 특성에 따른 주요 키워드를 추출하기 위해서는 래더링과 같은 기존의 계층적 단어 처리 방식보다는 단어를 계층적으로 분류하지 않는 접근법이 더 유용할 수 있다는 것을 실증적으로 보여주었다. 두 번째 연구 (N=50) 는 인터뷰를 구성하는 요소들에서 도출한 키워드들간의 차별성과

공통성을 함께 고려하는 것이 제품에 대한 사용자 경험을 심층적으로 파악하는데 유용하다는 것을 보여주었다.

제품에 대한 사용자 경험을 심층적으로 파악하는데 유용하다는 것을 보여주었다. 본 논문은 FIEM 의 유용성을 알아보기 위해 청소기에 대한 아마존 사용자 후기 (918 건) 자료와 FIEM 을 통해 얻은 인터뷰 (N=20) 자료의 결과를 비교하는 사례 연구도 수행하였다. 먼저, 두 자료에서 얻은 상위 키워드를 비교하여 FIEM 을 통해 도출한 키워드들과 아마존 사용자 후기에서 도출한 키워드들이 상당수 일치한다는 것을 확인하였다. 다음으로, 앞서 수행한 첫 번째와 두 번째 연구 결과에 기반하여 제품 사용 전, 중, 후에 형성되는 인상들과 공통적으로 관련된 키워드와 각 시점의 인상을 차별적으로 설명하는 키워드를 파악하였다. 그 결과, 제품의 첫인상에 주요 영향을 미치는 키워드는 기존의 연구 결과와 유사하게 제품의 외관과 밀접한 관련이 있다는 것을 확인 할 수 있었다.

본 논문은 주요 의의는 다음과 같다. 첫째, 이 논문은 제품의 첫인상을 단순히 순간적으로 발생하는 느낌이 아니라 제품과 직간접적으로 상호작용하면서 축적된 경험이라고 정의하고, 상호작용 시 발생하는 경험의 변화에 따라 제품의 첫인상을 이해할 수 있는 틀을 제공하였다. 둘째, 이 논문은 제품과 관련된 사용자 경험을 수집할 수 있는 방법을 제시하였을 뿐만 아니라 수집된 인터뷰 자료를 체계적으로 분석할 수 있는 방법도 함께 제시하였다. 하지만 이 논문은 기능적 제품에만 FIEM 을 적용해 보았다는 한계가 있다. 그러므로 향후에는 쾌락적, 미적 가치가 높은 제품 등에 FIEM 을 적용하여 제품의 첫인상을 규명하는 연구가 필요하다.

주요어: 제품의 첫인상, 역동적 사용자 경험, 사용자 인터뷰, 쾌락적·실용적 가치, 제품 디자인, 키워드 분석
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