International Journal of New Technology and Research(IJNTR)
ISSN:2454-4116, Volume-3, Issue-11, November 2017 Pages 94-100

Verification of the Factors of Quality Image Formation in Advanced Companies with Emotional Value

Takumi KATO, Kazuhiko TSUDA

***Abstract*—The concept of product quality is said to include not only objective value (functional value) such as performance and durability but also subjective value (emotional value) such as beauty and perceived quality. In recent years, companies such as Apple and Samsung, which have excellent emotional value, are emerging, which is a major source of competition in the manufacturing industry. However, few studies quantitatively verify the quality factor and composition ratio based on customer perceptions. Therefore, in this study, we verify these aspects based on customers' pure recall. Furthermore, we examine differences between advanced companies with emotional value and other companies.**

***Index Terms*—Brand image, Emotional value, Machine learning, Natural language processing, Pure recall, Quality**

I. INTRODUCTION

Quality in the manufacturing industry has long pointed to performance and durability. Since W. A. Shewhart of the American Bell Telephone Laboratories invented the control chart in 1926, statistical quality control has been actively carried out[1]. In the 1970s, the manufacturing industry in Japan started a production system called total quality control, and as a result of producing high-quality and high-performance products, the system spread worldwide[2]. In recent years, however, maintaining high technical quality has not necessarily led to high performance, and many Japanese manufacturing companies are now struggling[3].

Garvin argues that product quality has eight elements: performance, function, reliability, compatibility, durability, serviceability, beauty, and perceived quality[4]. Although beauty and perceived quality are difficult to measure, it is often that these are the biggest contributor to the hit[5]. Further, in recent years, their influence has been increasing.

In other words, the source of competitiveness has shifted from the functional value that can be evaluated by objective measures such as performance and durability to the emotional value (non-functional value) that customers feel subjectively such as beauty and perceived quality[3]. Nonetheless, there are cases in which manufacturers' engineers are allergic to things that can not be measured or can not be plotted, so emotional values are left behind[5].

In fact, companies such as Apple, Samsung, that emphasize emotional values such as design and user experience are emerging in the market. This is because as technology development progresses, product performance and durability exceed customer needs, thus no matter how much better it becomes, from the perspective of consumers, there is no difference. Therefore, commoditization occurs in the product market and price competition ensues. When products with high emotional value are introduced into such markets, customers welcome them.

Thus, product quality includes various elements. It has been stated that the concept of quality is totally abstract, complex, and various dictionary definitions are not particularly useful[5]. Further, few examples have been quantitatively verified. Therefore, in this study, using customers' perceptions, we quantitatively evaluate product quality and its composition ratio in terms of the eight quality factors discussed by Garvin. In addition, we verify the difference between advanced companies of emotional value such as Apple and Samsung and other companies.

By applying the methods used in this study, we can quantitatively understand the constituent factors included in the "quality" requested by customers regardless of the country or industry. This makes it possible to grasp the key points that companies should focus on in terms of the application of resources rather than conceptual levels such as functional value and emotional value.In this study, "brand" refers to the name of the company/product.

Takumi KATO,Business Development Supervisory Unit, Business Analytics Section, Honda Motor Co.,Ltd., Tokyo, Japan
Kazuhiko TSUDA, Graduate School of Business Sciences, University of Tsukuba, Tokyo, Japan

II. BRAND IMAGE

A. Quality and brand image

Table 1 shows the eight elements that comprise quality[4]. The breakdown consists of performance (Performance), which is the main feature of the product, in addition to features complementing the basic performance; reliability, indicating the probability of failure and repair frequency (Reliability); the degree of satisfying the probability criterion serviceability (Serviceability) such as conformance meaning conformance, durability indicating period of use until failure, serviceability such as ease of repair, beauty (Aesthetics) such as appearance, feel, sound, taste, and odor. Finally, there is perceived quality (Perceived Quality) such as brand image and advertisement. The concept whereby quality consists of the above eight elements is referred to as the Garvin theory hereafter.

Among these, the last two are the most subjective aspects, such as appearance, impression, sound, taste, smell. So these are matter of judgment of that person, it is nothing but a reflection of personal preferences. It turns out that this is the same concept as the emotional value described earlier[3].

However, to date, quantitative verification has not been performed on these eight elements.

Table 1: Garvin's eight elements of quality

No	Dimension	Difinition by Garvin
1	Performance	"Performance refers to a product's primary operating characteristics."
2	Features	"Features are the "bells and whistles" of products and services, those characteristics that supplement their basic functioning. "
3	Reliability	"This dimension reflects the probability of a product malfunctioning or failing within a specified time period. "
4	Conformance	"A related dimension of quality is conformance, or the degree to which a product's design and operating characteristics meet established standards. "
5	Durability	"Durability, then, may be defined as the amount of use one gets from a product before it breaks down and replacement is preferable to continued repair."
6	Serviceability	"A sixth dimension of quality is serviceability, or the speed, courtesy, competence, and ease of repair. "
7	Aesthetics	"Aesthetics—how a product looks, feels, sounds, tastes, or smells—is clearly a matter of personal judgment and a reflection of individual preference. "
8	Perceived Quality	"images, advertising, and brand names—inferences about quality rather than the reality itself—can be critical. "

In this study, rather than actually measuring the quality of the product, we quantitatively evaluate the customers' perceptions, that is, the brand image of quality.

Regarding quality and brand image, it has been shown that quality of service has a positive influence on brand image and customer satisfaction in the Thai automobile industry[6]. Aaker focuses on perceived quality, which is one of the major brand concepts, modeling the predictive factors and resulting factors of perceived quality, as shown in Fig. 1, to identify the role of perceived quality in the development of brand image Identify[7].

However, there are few examples that have quantitatively verified the constituent factors and composition ratios of the overall image of the concept of quality perceived by customers, which is the object of this study.

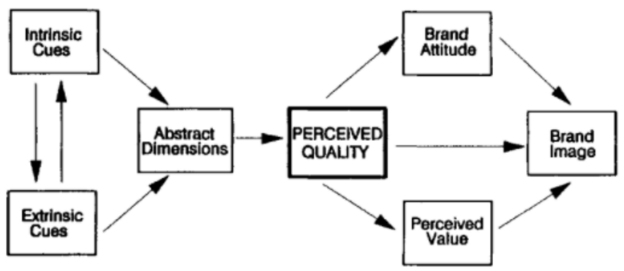

Fig. 1: The perceived quality model

B. *Typology of brand image*

Keller defines the brand image as "reflecting the brand association embraced by a consumer's memory for a certain brand"[8]. Brand personality is a concept that has been actively discussed in research on brand image. Aaker states that "It is defined as a set of human characteristics reminiscent of a given brand, and personality research is a theme that forms the core part of brand image research in a sense."[9]Aaker identifies the "Big 5" personality factors of sincerity, excitement, competence, sophistication, and ruggedness for American brands[10].

C. *Importance of pure recall*

In general brand image evaluation, there are many cases where data are obtained by preparing items supposed by companies and researchers and getting them to select respondents on the set scale (We call this assisted recall). The method of presenting options to respondents and asking them to match companies and products with images is called subsidization recall. One problem in subsidization recall is bias. Conversely, pure recall involves identification of a company or product image without the presentation of options to respondents. Therefore, pure recall is stronger in memory, bias is less and you can understand customers. Indeed, when confirming the brand image with assisted recall, it is verified that respondents overestimate[11]. In this study, to grasp the image of quality held by customers without bias, we should use pure recall to understand customers' perceptions.

III. VERIFICATION OF FACTORS COMPRISING THE "QUALITY"

A. *Outline of the study*

In this study, we examine two problem recognition scenarios.

In the first problem recognition scenario, the Garvin theory has been cast against the concept of quality, but there are few examples quantitatively evaluated. Therefore, Verification 1 evaluates factors constituting the quality brand image for customers and its composition ratio, and conducts comparative verification using the Garvin theory.

The second task recognition is that Adams appeals the importance of emotional value in the concept of quality[5], and Nobeoka cites Apple/Samsung as a representative example[3]. However, there are few examples of verifying differences from other companies. Therefore, in Verification 2, based on factors extracted by Verification 1, whether or not there is a difference between the above advanced enterprises and other companies is verified by whether or not they can be separated by machine learning. When they can be distinguished with a certain degree of precision, this means that there is a difference in the quality formation factors between the companies.

The outline of this study is shown in Fig. 2. Data are obtained across the country, and are questioned by "pure recall," "high-quality products/brands," and "reasons." At this point, the industry is not narrowed down, and generality is kept. Then, as preprocessing for extracting factors for Verification 1, text data outlining reasons for identifying high-quality brands are classified into quality elements of functional value and emotional value by natural language processing.

In this study, an "element" of quality means the word group defined from the customer's voice, and a "factor" of quality refers to the element group extracted by factor analysis.In addition, as shown in Fig. 3, the study process is largely composed of four phases. The first two are preprocessing and dictionary construction to understand the text obtained by pure recall and its text analysis, while the latter two involve carrying out the abovementioned verifications. Details of each phase are explained in the following sections.

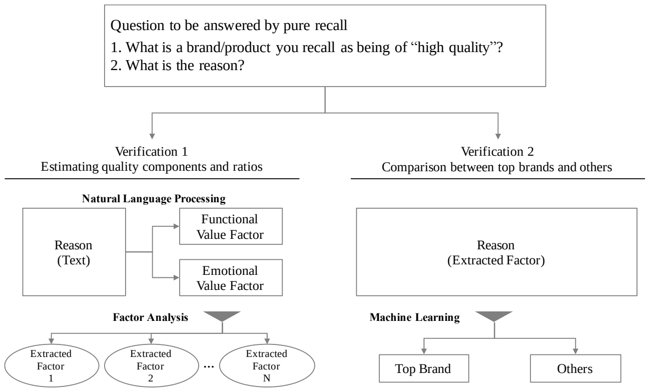

Fig. 2: Schematic diagram of the study

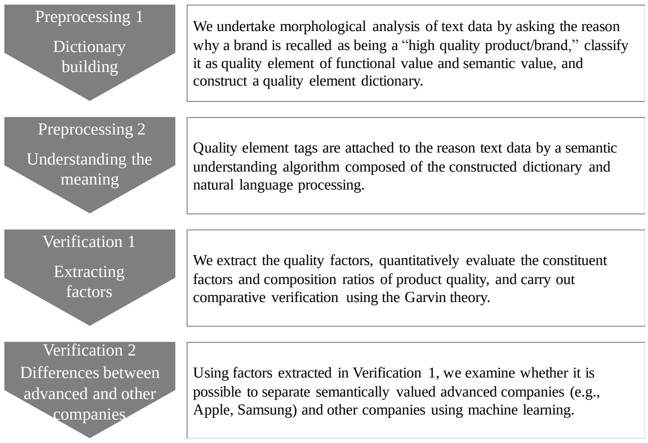

Fig.3: Study process

B. Study data

Table 2 shows the data used in this study. Data is Web survey conducted on 2017/5. The target countries were Brazil, China, Germany, India, Japan, South Africa, Thailand, the UK, and the USA. The industry was not specified. The sample size was 500 people in each country, totaling 4,500 people. The respondent attribute sets 10 groups of 2 gender (male and female) × 5 generations (20s–60s), and collects 50 people/groups of each country equally. As mentioned above, the questions involve two items based on pure recall, "brand/product remembered as being of high quality" and "reason for it." Since answers are written in multiple languages, native in national languages is analyzed after translating into Japanese.

Table 2: Data overview

Item	Content
Country	Brazil, China, Germany, India, Japan, South Africa, Thailand. UK, USA (9 countries)
Period	May 2017
Industry	Does not matter
Survey method	Web survey
Sample size	500 cases / country, Total 4,500 cases
Question	1. What is the brand / product recalled with "high quality" ? 2. What is the reason?

C. Preprocessing 1: Registering the semantic understanding dictionary

First, we constructed a dictionary to understand purely recalled text data. At this point, as noted before, since clear differences are evident between functional value and emotional value, they are distinguished and registered. In this study, objective words corresponding to facts and specifications are defined as subjective words corresponding to functional value, sensibility, and reputation as emotional value. For example, words such as "performance" and "durability" are functional values, while words such as "stylish" and "scent" are emotional values. Although we distinguish between the two values, we are able to use Verification 1 to understand whether factor analysis clearly divides customer perceptions.

Due to the nature of pure recollection, responses are almost always one sentence, at most two or three sentences. Further, the descriptions tend to be duplicated. As a result, the number of registered dictionary words is not very large.

After analyzing the 4,500 responses morphologically using the open source analysis engine MeCab, we found 13,351 words divided into 2,134 kinds of nouns and adjectives. Of these, 1,763 words and 2,572 words occurred less than five times. By arranging them in descending order of frequency and calculating the appearance coverage rate, as shown in Fig. 4, it was found that 351 kinds of words accounted for 80% of the total.

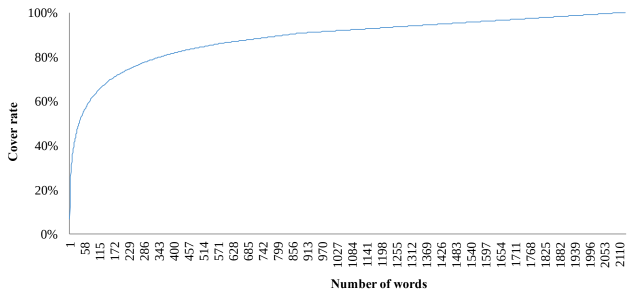

Fig. 4: Number of words and coverage of nouns and adjectives

Therefore, when registering an objective word as a functional value and a subjective word as an emotional value in order of frequency of words that appeared more than five times, there were 86 words in total. Table 3 shows the elemental structure of the dictionary and an example of each registered word. In addition, there were words such as "traditional" and "customer-oriented", but even if similar words are grouped together as elements, the composition ratio of quality elements described in Section IV is less than 30 that does not reach 1% And it is excluded. Further, because we are seeking to identify why a brand was identified as high quality, negative expressions are out of scope.

By the natural language processing of Preprocessing 2, the reason for raising the quality brand is categorized as the element of the quality registered here and given as a tag.

D. Preprocessing 2: Understanding the meaning of reason

A semantic understanding algorithm to understand the customer's colloquial voice is used. As a technique to understand spoken words, it is roughly divided into rule base and statistical meaning understanding. Tsuchiya judges emotions according to the rule of 8,024[12]. Harada uses statistical semantic understanding of, for example, LDA to understand spoken words[13]. In pure recall dealing with this research, since statistical processing is difficult because there are few words, we adopt the rule base approach. Another reason for adopting the rule base approach is that sentence expression is limited to quality brand image, so we do not need a large knowledge database.

In this study, based on the nature of the data obtained, we constructed the following four functions. Table 4 shows an analysis example. Note that the number of tags is scored in the case where the tag attached by grasping the dictionary registered word has a positive meaning.

As this data describes the reason after answering the brand, it is rare that the subject is clearly stated. Therefore, the function of the first "dependency" is focused on the affirmation/negation of the dictionary registration word, and when it is denied, no score is given. In the example in Table 4, because "reputation" and "durable" are affirmed, a score is given.

In the second function of "multiple negation", when words having negative meanings are arranged a plurality of times, it is finally judged whether or not it is affirmative and a score is given. Sixty-five negative words were registered including verbs such as "disgusting," "disappointed," and adjectives such as "bad," "terrible." In the example in Table 4, the reputation score is given because it is denied twice for "reputation."

The third " affirmative doubt" function is an algorithm that gives the score of the question-only sentences that are seeking synchronization. 4 words are registered. In the example in Table 4, although there are registered words "performance" "durability", "score is not given because it is a simple question"?

The function of the fourth "comparison" does not give a score in the context where another company or the past is better than understanding the dependency around "five" comparison words such as "more." In the example in Table 4, although "score performance" is inferior to "non-branded product," no score is given, but "taste" is added.

Natural language processing consisting of the above dictionary, morphological analysis, syntax analysis, and rules is called a semantic understanding algorithm. The environment is implemented in Python.

As confirmation of the accuracy of the semantic understanding algorithm, the relevance ratio and the recall ratio were evaluated using a total of 160 items including 10 elements. As shown in Table 5, the results are 96.9% and 93.8%, respectively, and thus the effectiveness of the algorithm is confirmed.

Table 6 shows the composition ratio of the result of tagging global data with the semantic understanding algorithm. Functional_ 01_Quality is the largest, followed by Functional_ 02 _ Durability, which is at the center of the quality image. Aggregating by value, the functional value is 61.9% and the emotional value is 38.1%.

In Verification 1, we compare and verify with Garvin theory by extracting factors from these 16 quality factors.

Table 3: Dictionary components and word examples

Value	Tag	Example Word 1	Example Word 2
Functional Value	Functional_01_Quality	Quality	High-quality
	Functional_02_Durability	Durability	Robustness
	Functional_03_Technology	Technology	Technical performance
	Functional_04_Function	Function	High-performance
	Functional_05_Safety	Safety	Safety performance
	Functional_06_Material	Material	Cloth
	Functional_07_Warranty	Warranty	Repair
	Functional_08_CostPerformance	Cost performance	Reasonable
Emotional Value	Emotional_01_Design	Design	Appearance
	Emotional_02_Feeling	Sound	Fragrance
	Emotional_03_Comfortable	Comfortable	Usability
	Emotional_04_Innovative	Innovative	Creative
	Emotional_05_Stylish	Stylish	Sophistication
	Emotional_06_Luxury	Luxury	Premium
	Emotional_07_Relief	Relief	Trust
	Emotional_08_Reputation	Reputation	Popularity

Table 4: Example of results of semantic understanding

Function	Text	Tag	Score
Dependency	Every product has high reputation and makes durable products.	Functional_02_Durability	1
		Emotional_08_Reputation	1
Multiple negation	Because the quality is wonderful and it has no bad reputation.	Emotional_08_Reputation	1
Positive doubt	Is it high performance, durability or what quality ?	Functional_02_Durability	0
		Functional_04_Function	0
Comparison	Compared with non-branded products, cost performance is lost, but the taste is overwhelmingly good.	Functional_08_CostPerformance	0
		Emotional_02_Feeling	1

Table 5: Conformity rate and recall rate of the semantic understanding algorithm

Value	Tag	Precision		Recall	
		Num	Correct	Num	Correct
Functional Value	Functional_01_Quality	10	10	10	10
	Functional_02_Durability	10	10	10	9
	Functional_03_Technology	10	10	10	10
	Functional_04_Function	10	10	10	7
	Functional_05_Safety	10	10	10	10
	Functional_06_Material	10	8	10	8
	Functional_07_Warranty	10	9	10	10
	Functional_08_CostPerformance	10	10	10	10
Emotional Value	Emotional_01_Design	10	10	10	10
	Emotional_02_Feeling	10	9	10	10
	Emotional_03_Comfortable	10	10	10	9
	Emotional_04_Innovative	10	10	10	9
	Emotional_05_Stylish	10	9	10	9
	Emotional_06_Luxury	10	10	10	10
	Emotional_07_Relief	10	10	10	10
	Emotional_08_Reputation	10	10	10	9
	Total	160	155	160	150
	Index	96.9%		93.8%	

Table 6. Global quality element tagging component ratio

Value	Tag	Score	Rate	Subtotal
Functional Value	Functional_01_Quality	992	32.9%	61.9%
	Functional_02_Durability	377	12.5%	
	Functional_03_Technology	155	5.1%	
	Functional_04_Function	105	3.5%	
	Functional_05_Safety	48	1.6%	
	Functional_06_Material	82	2.7%	
	Functional_07_Warranty	79	2.6%	
	Functional_08_CostPerformance	31	1.0%	
Emotional Value	Emotional_01_Design	64	2.1%	38.1%
	Emotional_02_Feeling	169	5.6%	
	Emotional_03_Comfortable	80	2.7%	
	Emotional_04_Innovative	104	3.4%	
	Emotional_05_Stylish	72	2.4%	
	Emotional_06_Luxury	108	3.6%	
	Emotional_07_Relief	280	9.3%	
	Emotional_08_Reputation	271	9.0%	
	Total	3,017	100.0%	100.0%

E. Verification 1: Factors constituting the quality image

In Preprocessing 2, factors that comprise the quality brand image are extracted following factor analysis of the tag score given by the semantic understanding algorithm.

An example of the data set as a result of applying the score is shown in Table 7. The number of respondents is 4,500, but there are cases in which a plurality of brands is listed at the time of reply and the reasons are described in common. In that case, the record is divided into the number of brands, and the reason text is stored the same. As a result, the total number of records is 5,590. In addition, the scores for the 16 quality elements defined in Table 3 are stored. The score is stored in a plurality of columns in one record when a plurality of quality elements are touched with one text. Those with a score of 2 or more are stored when the word of the same element registered in Preprocessing 1 is described more than once.

Factor analysis is carried out using the psych package of statistical software R and varimax rotation. The purpose of direct rotation is to eliminate correlations between factors and to extract factors with a high degree of uniqueness. In addition, the number of factors to be extracted is determined by drawing a scree plot and delimiting factors with eigenvalues greater than 1.0.

Table 7: Examples of data sets with scores

Record	Respondent No	Reply Brand	Functional_01_ Quality	Functional_02_ Durability	Functional_03_ Technology	. . .	Emotional_08_ Reputation
1	1	Apple	1	0	0		0
2	2	Nestle	0	0	1		0
3	2	Toyota	0	0	1		0
4	3	NIKE	0	1	0		2
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
5590	4,500	Samsung	0	0	0		0

F. Verification 2: Differences between advanced companies with emotional value and others

Finally, we examine whether there is a difference between advanced companies with emotional value and other companies. Before entering the verification, I have mentioned Apple and Samsung as advanced companies of emotional value[3], but to confirm whether it can actually be listed as a top quality brand There is a need.

Table 8 shows the composition ratio of the top 30 global brands listed in pure recall in each country. Apple and Samsung are outstanding, both having elicited more than 10% globally. As for the difference between the two companies, Apple has a high score overall, although there are slight fluctuations, while although Samsung has a low presence in China and Japan, we can see the strength of the market. In addition, Apple is the only company to remember product brand iPhone.From the above, both Apple and Samsung, which were exemplified[3], have confirmed the superiority of the survey, and thus both companies are defined as advanced companies with emotional value.

To estimate companies similar to Apple/Samsung, hierarchical clustering using the Ward method is performed using the factor scores and standard deviations. The environment is the hclust package of the statistics software R. As shown in Fig. 5, looking at the results with a dendrogram, we can see that Apple and Samsung are adjacent and have similar characteristics to several other companies. Philips and Google closely resemble both companies, and it seems that they have the potential to become an advanced company with emotional value.

Table 8: Top 30 brands recalled with quality images

No	Brand	Brazil	China	Germany	India	Japan	South Africa	Thailand	UK	USA	Global
1	**Samsung**	**25.2%**	**1.1%**	**11.6%**	**15.6%**	**0.0%**	**18.3%**	**19.0%**	**13.5%**	**14.6%**	**11.0%**
2	**Apple**	**12.0%**	**21.1%**	**10.4%**	**12.4%**	**8.2%**	**8.1%**	**16.8%**	**21.3%**	**13.9%**	**10.7%**
3	SONY	6.1%	1.8%	9.4%	9.1%	5.8%	6.1%	4.7%	12.9%	8.8%	5.9%
4	NIKE	4.3%	3.9%	4.0%	5.2%	1.4%	6.3%	2.2%	5.7%	10.4%	4.1%
5	adidas	2.1%	1.8%	6.9%	5.2%	0.5%	5.1%	2.9%	2.6%	3.0%	3.0%
6	Nestle	17.2%	0.8%	0.7%	3.0%	0.5%	6.9%	1.1%	1.1%	0.5%	2.8%
7	BMW	1.5%	2.4%	7.9%	1.2%	1.0%	7.3%	5.1%	2.6%	2.6%	2.8%
8	LG	4.3%	0.3%	1.5%	5.5%	0.5%	8.5%	0.4%	1.4%	4.4%	2.8%
9	Mercedes-Benz	0.6%	2.4%	9.4%	1.5%	4.8%	1.2%	9.5%	0.3%	0.2%	2.3%
10	Unilever	2.5%	0.3%	0.0%	3.3%	0.0%	4.3%	1.8%	1.1%	1.6%	1.5%
11	Panasonic	0.9%	2.1%	2.2%	1.0%	7.7%	0.8%	1.5%	3.7%	0.7%	1.5%
12	Microsoft	4.0%	1.3%	0.5%	2.4%	0.0%	1.2%	0.0%	2.3%	3.7%	1.5%
13	HUAWEI	0.0%	17.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.4%
14	**iPhone**	**0.9%**	**1.3%**	**1.0%**	**1.6%**	**2.4%**	**1.2%**	**9.5%**	**0.6%**	**0.5%**	**1.4%**
15	Haier	0.0%	16.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.4%
16	Google	2.5%	0.3%	0.5%	4.8%	0.0%	0.2%	0.7%	1.1%	2.3%	1.3%
17	CHANEL	0.3%	0.5%	0.7%	0.3%	7.2%	0.4%	4.4%	3.7%	1.6%	1.3%
18	Philips	0.3%	2.1%	3.0%	4.6%	0.0%	0.6%	0.0%	0.0%	0.0%	1.2%
19	Lenovo	0.3%	9.5%	0.5%	0.7%	0.0%	0.6%	0.0%	0.3%	0.7%	1.1%
20	VW	1.5%	1.8%	3.0%	0.4%	0.0%	4.3%	0.0%	0.3%	0.2%	1.1%
21	Bosch	0.0%	0.3%	6.9%	0.1%	0.0%	2.6%	0.0%	1.7%	0.2%	1.1%
22	Coca-cola	3.7%	0.5%	1.2%	0.4%	0.0%	2.2%	0.4%	1.1%	2.3%	1.1%
23	DELL	3.4%	0.8%	0.5%	2.7%	0.0%	1.6%	0.7%	0.0%	0.9%	1.1%
24	GUCCI	0.0%	0.5%	0.2%	0.1%	3.4%	0.4%	2.6%	3.4%	2.8%	1.0%
25	ROLEX	0.0%	0.3%	0.5%	1.0%	2.9%	0.8%	1.8%	4.0%	0.7%	0.9%
26	Ford	0.3%	0.5%	0.5%	0.7%	0.0%	2.4%	1.1%	1.4%	2.8%	0.9%
27	Amazon	0.0%	0.3%	1.5%	2.2%	0.0%	0.0%	0.0%	2.9%	2.1%	1.0%
28	VUITTON	0.0%	0.8%	0.0%	0.1%	11.1%	0.0%	2.6%	0.6%	1.2%	0.9%
29	Audi	0.0%	1.3%	5.9%	1.3%	0.5%	0.2%	0.0%	0.0%	0.0%	0.7%
30	P&G	0.3%	0.0%	0.5%	0.7%	0.0%	1.8%	0.7%	0.0%	3.5%	0.7%
	The others	5.8%	6.6%	9.1%	12.5%	42.0%	6.7%	10.6%	10.1%	13.7%	30.3%
	Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

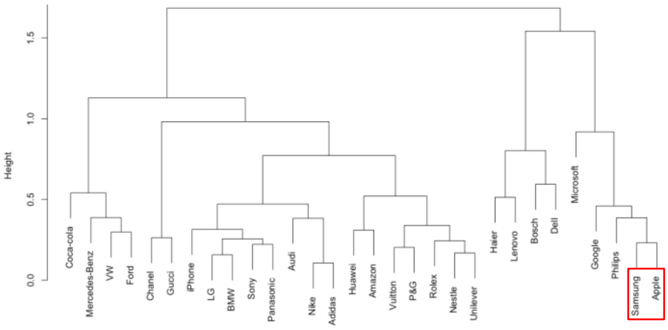

Fig. 5:Dendrogram by hierarchical clustering

As mentioned above, although the similar characteristics of Apple/Samsung can be understood from the dendrogram, it is not certain whether they can be clearly identified by machine learning. Therefore, in Verification 2, the support vector machine (SVM) is used to verify the separation accuracy between advanced enterprises with emotional value and other companies. In addition to Apple and Samsung, iPhone is included as an advanced company brand.

However, as shown in Table 8, even if the above three brands are combined, only 23.1% is reached, so it is understood that it is imbalance data. Classification of imbalance data by SVM as it is will result in ignoring labels of smaller companies, that is, labels of advanced companies with emotional value. Therefore, negative examples are reduced using random undersampling, and the composition ratio of positive examples to negative examples is verified as

1:1.

IV. VERIFICATION RESULTS AND DISCUSSION

A. Verification 1: Factors constituting the quality image

A scree plot is outputted to determine the number of factors extracted by factor analysis from the 16 quality factors. As shown in Fig. 6, the number of factors whose eigenvalues are 1.0 or more is eight, and thus this number is adopted.

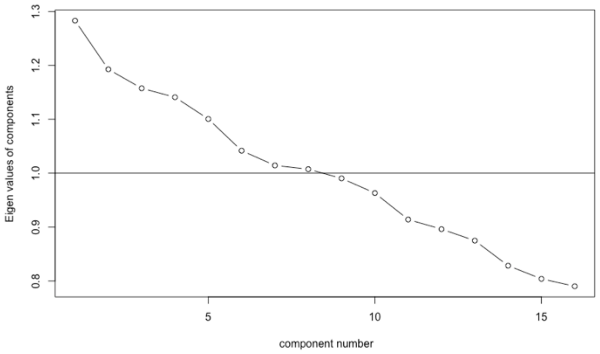

Fig. 6: Scree plot

The factor loading amount obtained from the factor analysis is shown in Table 9. Table 10 shows the named factors, the contribution rate, the explanatory rate, and the correspondence between the eight quality factors of Garvin, based on factors with a high factor loading. The cumulative contribution rate is 34.3%, because the nature of pure recall is such that it is likely that many elements are written at the same time.

Of the eight factors, Safety, Material, Warranty, and Durability are composed of functional values, and the cumulative explanation rate is 64.10%. It is also associated with the Garvin theory. Conversely, Design and Reputation correspond to Aesthetics and Perceived Quality, but no Innovative and Technology of Innovative & Comfortable are found to be applicable. In other words, the functional value that the manufacturing industry has emphasized for a long time still serves as the basis of the quality brand image, but in recent years factors relating to emotional value such as Innovative and Comfortable have increased in importance.

The result that the functional value is more than 60% and the emotional value is less than 40% is the same in terms of the frequency of the quality factor in Table 6. In other words, in this study, we adopted the factor analysis approach to narrow down the number of factors, but it seems that the presence of emotional value is about 40%.

Table 9: Factor loading

Value	Factor	ML4	ML3	ML1	ML2	ML6	ML5	ML7	ML8	h2	u2	com
Functional Value	Functional_01_Quality	0.00	0.02	0.09	-0.02	0.03	0.03	-0.04	0.20	0.05	0.95	1.59
	Functional_02_Durability	-0.01	0.04	0.04	0.00	0.06	0.72	0.02	0.00	0.52	0.48	1.03
	Functional_03_Technology	0.02	0.00	0.01	0.07	0.02	-0.03	0.38	0.03	0.15	0.85	1.10
	Functional_04_Function	0.04	0.02	-0.02	-0.01	0.02	0.06	0.01	0.08	0.01	0.99	2.93
	Functional_05_Safety	1.00	0.02	0.05	-0.01	0.00	0.01	0.03	0.02	1.00	0.01	1.01
	Functional_06_Material	-0.02	0.99	-0.01	0.03	0.05	0.04	0.01	-0.06	1.00	0.01	1.02
	Functional_07_Warranty	0.01	0.00	0.99	-0.01	-0.02	-0.01	0.03	0.09	1.00	0.01	1.02
	Functional_08_CostPerformance	-0.01	0.09	0.01	0.09	-0.02	0.01	-0.05	-0.07	0.02	0.98	3.52
Emotional Value	Emotional_01_Design	-0.01	-0.02	0.00	0.00	0.71	-0.01	0.02	0.00	0.50	0.50	1.00
	Emotional_02_Feeling	0.01	0.04	-0.01	-0.01	0.01	-0.01	-0.01	-0.09	0.01	0.99	1.49
	Emotional_03_Comfortable	0.02	-0.03	-0.01	0.03	0.04	0.03	0.25	-0.08	0.07	0.93	1.36
	Emotional_04_Innovative	0.00	0.02	-0.03	0.96	0.05	-0.03	0.24	0.13	1.00	0.01	1.18
	Emotional_05_Stylish	-0.01	0.02	-0.01	0.01	0.26	0.01	0.02	0.01	0.07	0.93	1.03
	Emotional_06_Luxury	0.00	-0.01	-0.01	0.05	0.03	-0.06	-0.08	-0.04	0.02	0.99	3.45
	Emotional_07_Relief	0.07	-0.02	-0.02	0.00	-0.04	0.07	0.02	0.00	0.01	0.99	2.97
	Emotional_08_Reputation	0.00	-0.01	-0.03	0.02	-0.03	-0.05	-0.01	0.30	0.09	0.91	1.09
Index	SS loadings	1.00	1.00	1.00	0.93	0.59	0.54	0.28	0.18	-	-	-
	Proportion Var	0.06	0.06	0.06	0.06	0.04	0.03	0.02	0.01			
	Cumulative Var	0.13	0.06	0.19	0.25	0.28	0.32	0.33	0.35			
	Proportion Explained	0.18	0.18	0.18	0.17	0.11	0.10	0.05	0.03	-	-	-
	Cumulative Proportion	0.36	0.18	0.54	0.71	0.82	0.92	0.97	1.00	-	-	-

Table 10: Comparison of extract factor and Garvin theory

No	Extracted Factor	8 Dimensions of Quality by Garvin	Proportion Var	Proportion Explained
1	Safety	Performance	6.2%	18.1%
2	Material	Features	6.2%	18.1%
3	Warranty	Serviceability	6.2%	18.1%
4	Innovative	–	5.8%	16.9%
5	Design	Aesthetics	3.7%	10.6%
6	Durability	Reliability, Durability	3.4%	9.8%
7	Technology of Innovative & Comfortable	–	1.7%	5.1%
8	Reputation of Quality	Perceived Quality	1.1%	3.3%
		Conformance		
	Total		34.3%	100.0%

B. Verification 2: Differences between advanced companies with emotional value and others

We introduce factor scores to the SVM and judge whether they are advanced companies with emotional value or not. The environment is the e1071 package of statistical software R, and the parameter settings are shown in Table 11.

As already mentioned, since these data are positive examples, that is, imbalance data having a small number of records of advanced enterprises with emotional value, negative examples are reduced by random undersampling. As shown in Table 12, because 1,039 out of 5,590 cases are positive, the same number is randomly sampled from 4,551 negative cases. Then, random sampling is performed using the 2,078 positive/negative examples, and 90% is set as learning data and 10% is set as verification data.

Table 11: SVM parameters

SVM-Type	C-classification
SVM-Kernel	radial
cost	1
gamma	0.125

Table 12: Results of random undersampling

Data	Num	Rate
Total	5,590	
- Positive	1,039	18.6%
- Nrgative	4,551	81.4%
Training/Predicting	2,078	
- Positive	1,039	18.6%
- Nrgative	1,039	18.6%

First, for comparison, 90% of the 5,590 cases is learned, and 10% is randomly sampled as verification data to confirm accuracy. As shown in Table 13, almost all data are predicted to be negative examples, and the detection accuracy of positive examples is only 7.8%. Next, we tried to improve the detection accuracy of the positive example by using random undersampled data. As a result, as shown in Table 14, although the overall accuracy decreased to 78.4%, the detection accuracy of the positive example improved to 63.0%.

Table 13: Result by all

		Prediction 0	Prediction 1	Correct rate
Actual data	0	448	9	98.0%
	1	94	8	7.8%
Total Correct Rate				81.6%

Table 14: Result by undersampled

		Prediction 0	Prediction 1	Correct rate
Actual data	0	87	17	83.8%
	1	38	66	63.0%
Total Correct Rate				78.4%

Due to the nature of the pure recall data, the separation accuracy is only 78.4% because there are only a few variables exposed in one record, but it can be determined without using other explanatory variables such as text proper nouns and customer attributes. Thus, it is possible to confirm the difference between advanced companies with emotional value and other companies. Of course, if words that make it easier to identify Apple/Samsung such as “smartphone” and “IT” are incorporated into the model, further improvement in accuracy can be expected, but because such hard coding does not suit the purpose of this study, verification is completed here.

V. Conclusion

The contribution of this study is the source of competitiveness for the manufacturing industry based on quantitative assessment globally, regardless of the industry, of constituent elements and ratios for quality, which is an obscure concept. Functional factors such as Safety, Material, Warranty, and Durability are on a continuous basis, but factors such as Innovative and Technology of Innovative & Comfortable, which were not clearly discussed in the Garvin theory, I understood that it is included in perception.

In addition, we focused on the concept of emotional value in which the importance is appealed more than functional value in the creation of value of goods and services. As a good example embodying emotional value, the name of Apple/Samsung gets well, but also in customer perception, it shows pure recall that it can be cited as an excellent company. Furthermore, the study reveals a difference from other companies from the viewpoint of discrimination using machine learning techniques.

In this study, although the elements necessary for quality may be known, it is difficult to understand what kind of approach a company should actually take. Therefore, the challenge is to grasp not only products and services, but also advertisements and events, from where to feel the brand image elements of quality specifically.

Even for words that everyone knows of quality, the elements perceived by the customer seem to change depending on the times. After 10 years, it is likely that there is a big change from the contents verified in this study. Therefore, before making decisions on business investment, companies should quantitatively determine the brand image that they wish to promote using the approach outlined in this study.

References

[1] B. Klefsjo, B. Bergquist, R. Edgeman,“Six sigma and total quality management: different day, same soup? International Journal of Six Sigma and Competitive Advantage”, 2(2), 2006, pp. 162-178.
[2] H. Sun, “The patterns of implementing TQM versus ISO 9000 at the beginning of the 1990s”, International Journal of Quality & Reliability Management, 16(3), 1999, pp. 201-215.
[3] K. Nobeoka, “Value Creation and Value Capture at Manufacturing Firms: Importance of Non-functional Value”, Institute of Innovation Research, Hitotsubashi University Working Paper, 2010, 10-01.
[4] D. Garvin, “Competing on the eight dimensions of quality”, Harvard Business Review, 1987, November–December.
[5] J. Adams, “Good products, bad products: Essential elements to achieving superior quality”, McGraw-Hill Education, 2012.
[6] T. Vigripat, P. Chan, “An empirical investigation of the relationship between service quality, brand Image, trust, customer satisfaction, repurchase intention and recommendation to others”, International DSI/Asia and Pacific DSI, 2007.
[7] D. Aaker, “Brand equity and advertising: Advertising’s role in building strong brands”, Psychology Press, 2013. pp. 143-161.
[8] K. Keller, M. Parameswaran, I.Jacob,“Strategic brand management: Building, measuring, and managing brand equity”, Pearson Education India, 2011.
[9] D. Aaker, “Building strong brands”, New York, NY: Simon and Schuster, 1996.
[10] J. Aaker, “Dimensions of brand personality”, Journal of Marketing Research, 34(3), 1997, pp. 347-356.
[11] F. Kardes, D. Sanbonmatsu, M. Cronley, D. Houghton, “Consideration set overvaluation: When impossibly favorable ratings of a set of brands are observed”, Journal of Consumer Psychology, 12(4), 2002, pp. 353-361.
[12] S.Tsuchiya, M.Suzuki, M.Imono, E.Yoshimura, H.Watabe, “Emotion judgement method based on knowledge base and association mechanism for colloquial expression”, The Japanese Society for Artificial Intelligence, 29(1), 2014, pp. 11-20.
[13] T.Harada, N.Suzuki, Y.Fujita, K.Tsuda, “The estimate method of the omission of Japanese inquiry texts using an LDA algorithm”, International Journal of Computer Applications in Technology, 52(2–3), 2015, pp. 186-195.