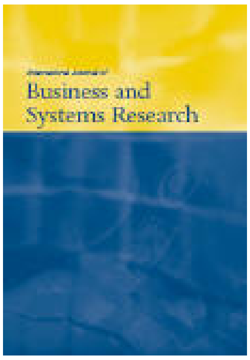

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Takayuki Suzuki, Kiminori Gemba, Atsushi Aoyama

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Information discovery methods using statistical processing to facilitate innovation creation

Takayuki Suzuki*

Department of Business Administration,
Kyoto University of Advanced Science,
18 Gotanda-cho, Yamanouchi,
Ukyo-ku Kyoto, 615-8577, Japan
Email: suzuki.takayuki@kuas.ac.jp
*Corresponding author

Kiminori Gemba

Business School of Innovation Management,
Hosei University,
3-3-9 Kudankita, Chiyoda-ku,
Tokyo 102-0073, Japan
Email: gemba@hosei.ac.jp

Atsushi Aoyama

Graduate School of Technology Management,
Ritsumeikan University,
2-150 Iwakura, Ibaraki Osaka, 567-8570, Japan
Email: aoyama@mot.ritsumei.ac.jp

Abstract: In the past, products were classified by hand, using qualitative judgement. This research proposes a method of discovering information that facilitates the creation of innovation using statistical processing, and an external theory targeting information associated with products. Word-of-mouth information concerning home appliances, aggregated during a specific period, was collectively analysed without dividing the total duration of the period. It was found that information lead to the emergence of innovation. This study aimed to discover information that supplements innovation through statistical processing (i.e., principal component analysis, non-negative matrix factorisation, and latent Dirichlet allocation). In the future, it will be crucial to re-examine various discussions that can be expressed in two dimensions or those that independently deal with product characteristics. Going forward, it will be essential to perform quantitative analysis of the relationship of product characteristics with each period of the product life cycle.

Keywords: information discovery methods; statistical processing; innovation creation; product characteristics; product life cycle; aesthetics; quantitative analysis; principal component analysis; latent Dirichlet allocation; non-negative matrix factorisation; NMF; Bass model.

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Biographical notes: Takayuki Suzuki is a Junior Associate Professor in the Department of Business Administration at Kyoto University of Advanced Science. His research interests include innovation management and web marketing and natural language analysis, among others. He was conferred his Master's degree from the Graduate School of Technology Management at Ritsumeikan University. In 2014, he joined Murata Machinery, where he worked in the departments of IT solutions, purchasing, and production engineering. In 2021, he received his PhD from the Ritsumeikan University.

Kiminori Gemba is a Professor at the Business School of Innovation Management at Hosei University. His research interests are innovation theories and strategic management. In 1992, he received his Master's in Engineering from the University of Tokyo. He joined the research division of Sanwa Research Institute and his research focused on environmental management and new industry creation. He received his PhD from the University of Tokyo in 1999. Subsequently, he became a research associate and an Associate Professor at the University of Tokyo and a Professor at the Ritsumeikan University.

Atsushi Aoyama is a Professor at the Management of Technology at Ritsumeikan University. After graduating from Kyoto University with a degree in Chemical Engineering, he was engaged in research at Mitsubishi Research Institute on a systems approach to connect society's needs with advanced technology. He received his PhD from Purdue University in 1994. In 1995, he became a Research Fellow at the Imperial College, University of London. From 1999 to 2005, he served as an Assistant Professor at the Research Institute of Resources and Chemistry, Tokyo Institute of Technology. He has been a Professor at the Ritsumeikan University's Graduate School of Technology Management since 2005. He was the Former Chairman of the Safety Committee of the Chemical Engineering Society. He is the Director of the Inamori Business Philosophy Research Centre, Ritsumeikan University (since 2015). He also serves as an Outside Director of Kyocera Corporation (since 2016).

1 Introduction

Innovation ensures that companies grow and develop sustainably. A prime reason to innovate is the attainment of competitive advantage. Simply developing and producing existing products in a better way has proven to be inadequate in this regard. Instead, it is important to establish a competitive advantage both by developing and producing products that bring new value to customers and by creating new mechanisms to secure profits. If companies do not adopt novel evidence-based measures, they will not be able to secure a competitive advantage that facilitates sustainable growth.

Over the years, the diffusion of the internet and its related devices has led to a myriad of text information accumulation on the internet. Hence, it is difficult to manually analyse this information. Relying on traditional methods is not only time-consuming and expensive, but also the analysis might not be viable.

Therefore, new methods of automating analysis using machines, such as artificial intelligence (AI), are drawing attention. In fact, the creation of new services that use data and digital technology is becoming increasingly active. Moreover, only a few studies target marketing in this regard. Unless applicability in relation to marketing activities is expanded, the current situation cannot be grasped quickly and accurately. This results in the delay and stagnation of the emergence of innovation.

This study aims to propose a method of discovering information that facilitates the emergence of innovation by analysing big data using statistical processing, which cannot be conducted by humans without adequate computational tools.

First, this study delves into previous studies. Next, it proposes research questions and hypotheses based on the limitations of the current evidence base. Experiment and discussions concerning the two proposed methods are conducted to verify the research questions and hypotheses. Finally, the academic and practical implications, limitations, and future implications of this study are explained.

2 Literature review

2.1 Concept of value

Although various concepts of value exist, this study presents examples derived from consumer behaviour. According to Hirschman and Holbrook (1982, pp.92–101), a hedonic benefit 'designates those facets of consumer behaviour that relate to the multisensory, fantasy, and emotive aspects of one's experience with products. Holbrook et al. (1982) claimed that a product can be represented in two dimensions: hedonic and utilitarian benefits. According to Chitturi et al. (2008, p.50), utilitarian benefits are 'the functional, instrumental, and practical benefits of consumption offerings'. Specifically, hedonic benefits are judged subjectively, whereas utilitarian benefits are judged objectively.

A value can be expressed in two dimensions. Woodruff (1997) noted that there are various definitions of customer value. Particularly, the terms utility, worth, benefits, and quality are often used but are not clearly defined. In fact, the definitions of Chitturi et al. (2008) and Holbrook et al. (1982) are imprecise and ambiguous. In other words, it is difficult to quantitatively classify products and their characteristics into two dimensions based on such definitions because they differ depending on the person classifying them. Therefore, the next section reviews previous studies that examined whether diverse sources of value (i.e., products and product characteristics) can be classified quantitatively.

2.2 Classification of value

Batra and Ahtola (1991) used the semantic differential (SD) method and factor analysis, to denote that products can be represented in two dimensions: hedonic and utilitarian benefits. They prepared a rating scale, with indicators such as pleasant-unpleasant/ good-bad, and rated 56 respondents on a seven-point scale for Pepsi, Listerine, Comet cleanser, and Cadillac brands. Factor analysis was performed by combining the four brand results. In most cases, two-factor structures emerged. The first and second factors comprised hedonic (e.g., pleasant, nice) dimensions and utilitarian (e.g., useful, beneficial) aspects respectively. Thus, it was clarified that the product can be expressed in both dimensions. Moreover, they proposed the following SD items employed to measure the utilitarian elements of brand attitude: 'useful/useless', 'valuable/worthless', 'beneficial/harmful', and 'wise/foolish'. Further, the SD items for measuring the hedonic elements of brand attitude were 'pleasant/unpleasant', 'nice/awful', 'happy/sad', and 'agreeable/disagreeable'. The brand of the product was targeted as a result, and the interpretation of the scale of hedonic and utilitarian elements was rendered ambiguous. Crowley et al. (1992) used the eight SD items proposed by Batra and Ahtola (1991) and then used product categories rather than product brands to perform more rigorous testing to verify the reliability and effectiveness of the scale of hedonic and utilitarian elements. Specifically, a questionnaire survey was administered on 151 students with eight SD items, and factor analysis was conducted based on the survey's results. When all 24 product categories were combined, it could be expressed by two factors. However, when implemented without the combination procedure, only 12 product categories could be expressed by two factors (e.g., soft drinks, potato chips, and cooking oil). In addition, seven product categories could be represented by one factor (e.g., chewing gum, microwave popcorn, and peanut butter). Finally, five product categories could be expressed by three factors (e.g. ice cream, chocolate, candy bars), suggesting that the SD item needs to be reviewed for generalisation.

The studies mentioned above relate to whether product brands and product categories can be quantitatively classified as providing hedonic or utilitarian benefits. However, the next study focuses on product characteristics. Goto et al. (2019, pp.33–43) studied the evaluation points (i.e., image quality, battery, functionality, design, sense of hold, operability, liquid crystal, and portability) of digital cameras at Kakaku.com, which is a word-of-mouth website for home appliances. The first factor was 'image quality, operability, battery, functionality, liquid crystal, and sense of hold' (index related to functionality), and the second factor was 'design and portability' (visual information on the appearance of the product). Nevertheless, the load of 'image quality and sense of hold' was positive for both factors. While relying on the concept of cognitive response, the authors showed that 'design and portability' could be categorised as an aesthetic interpretation, and 'image quality and sense of hold' could be classified as a symbolic interpretation.

Arruda-Filho (2019) argued that in current mobile phones, most of the on-board features have hedonic nuances (e.g., MP3 players, cameras, internet access). More generally, as multifunctional products provide multiple types of value or functionalities that consumers can perceive, they go beyond utilitarian benefits to create a sense of enjoyment and personal satisfaction (hedonic benefits). Therefore, the study points out that consumer prefer mobile phones with multiple functions listed due to the hedonic benefits.

Baltas et al. (2017) noted that the utilitarian-hedonic benefits distinction between products does not allow many products to be categorised as being entirely utilitarian or hedonic. They point out that some products may provide both utilitarian and hedonic benefits.

Voss et al. (2003) used confirmatory factor analysis to classify products into four quadrants based on high and low hedonic and utilitarian benefits. The low hedonic and high utilitarian quadrant includes shoelaces, paper clips, disposable baby diapers, and alkaline batteries. The high hedonic and high utilitarian quadrant includes automobiles, athletic shoes, blue jeans, television sets, and vacation resorts. The low hedonic and low utilitarian quadrant includes glass figurines, fake moustaches, plastic fruit, pet rocks, and tobacco. The high hedonic and low utilitarian quadrant includes beer and video games.

Volz and Volgger (2022) categorised the lodging concept into utilitarian and hedonic benefits. Focussing on advertising for Airbnb and boutique hotels, they found no difference between emotional and rational appeals for Airbnb. In the case of boutique hotels, however, emotional advertisements tend to be more effective than rational ones. Thus, Airbnb combines both utilitarian and hedonic benefits, while boutique hotels are categorised as providing hedonic benefits.

Akdim et al. (2022) targeted social mobile apps. Using the SD method, they found that TripAdvisor is a utilitarian-benefit app and Instagram is a hedonic-benefit app. They also found that perceived enjoyment was important for Instagram and ease of use was important for TripAdvisor.

Thus, previous analyses on product brands, categories, or characteristics have categorised them into two types: those providing hedonic and utilitarian benefits. However, it is difficult to classify product characteristics into only two factors; instead, it is necessary to classify them into multiple factors. Moreover, analysis on product brands, categories, or characteristics only quantitatively verifies which value can be classified and does not affirm whether it leads to innovation. In addition, utilitarian and hedonic benefits are treated independently, and have not been investigated in an integrated manner.

Some studies have applied hedonic and utilitarian benefits to purchasing. Rudawska et al. (2015) administered a questionnaire survey and factor analysis on users who practised group buying and suggested that customers perceive the value they get from shopping in terms of functional and hedonic benefits. This was applied to products, product functions, and purchases. Studies have used the concepts of hedonic and utilitarian benefits to identify different information channels for making purchases. Li et al. (2020) found that information channel choice varies significantly between hedonic (e.g., toys) and utilitarian (e.g., office supplies) purchases. When consumers make hedonic purchases, they use social media and product pages on a website two weeks before the final purchase. In contrast, for utilitarian purchases, consumers use third-party reviews up to two weeks before the final purchase, and revealed that they use search engines, deals, and competitors' product pages more frequently as the time of purchase approaches. Zhao et al. (2020) conducted a study to examine how the price of a product affects consumer purchasing behaviour in the categories of hedonic and utilitarian benefits. They targeted higher priced laptop computers (a high-priced product) and lower priced mobile phones (a low-priced product). When the price of the product is high, loss concern is high, and consumers tend to focus on utilitarian benefit items to avoid potential losses. When the price of the product is low, loss concern is low, and consumers tend to choose items of hedonic benefit.

Some studies have revealed that marketing promotions differ by product categories based on hedonic and utilitarian benefits. Narayanaswamy and Heiens (2018) suggested that the sales promotion mechanisms preferred by marketers of hedonic products but used less by marketers of utilitarian products are price and gift promotions, and sweepstakes and contests. In contrast, the only promotional mechanism equally preferred by marketers of both hedonic and utilitarian products, is the limited hour special.

Choi et al. (2006) found that products can be classified into four categories, namely complex, intelligent, light, and simple, typified by rings, notebook computers, toys, and copy paper, respectively. Hassenzahl et al. (2010) proposed that the sources of positive experiences with interactive products and technologies (e.g., mobile phones, MP3 players, and navigation devices) can be categorised into seven types: competence, relatedness, popularity, stimulation, meaning, security, and autonomy.

Arboleda and Arce-Lopera (2015) reported that soft drink bottles can be categorised based on their shape. They found that the width of the lid and the sharpness of the body are important visual cues for categorisation. Holy et al. (2017) proposed a method to classify products based on their co-occurrence by applying a genetic algorithm to data from market baskets (combinations of products that are likely to be purchased together, such as beer and diapers).

Singh and Tucker (2017) pointed out that in online shopping, products need to be classified by three direct product characteristics (form, function, or behaviour), two indirect product characteristics (function or behaviour), and another two indirect product characteristics (service and other). Service refers to elements that are indirectly related to the product and that affect the customer's experience, such as delivery, packaging, and product changes. For example, 'the packaging was not adequate' represents an opinion about the service provided by the seller.

Frank et al. (2021) found that AI products can be categorised into utilitarian, hedonic, and symbolic dimensions. Furthermore, they showed that both hedonic and symbolic dimensions have a much stronger effect on the demand for AI products than that of the utilitarian dimension. According to Smith and Colgate (2007), the symbolic dimension is concerned with the extent to which customers attach or associate psychological meaning to a product. Frank et al. (2015) found that the use of the latest innovative products leads to an innovative self and social image. Yun and Geum (2020) used latent Dirichlet allocation (LDA) to automatically classify patents.

Some studies focus specifically on service characteristics. Arcand et al. (2017) found that in mobile banking service quality, utilitarian benefits consist of efficiency, productivity, security, and suitability; however, they found that hedonic benefits consist of enjoyment, social experience, and so on.

2.3 Bass innovation diffusion model

The product life cycle is the period from when a product enters the market to when it leaves the market. Since the product life cycle cannot be quantitatively classified into each period, the Bass model and Bass innovation diffusion model must be introduced to address this problem. Another problem with the product life cycle is that each period cannot be arranged quantitatively. The studies that relate each period of the product life cycle to the product characteristics are outlined next.

The following is a description of the Bass model and Bass innovation dissemination model. Bass (1969) mathematically formulated that the product life cycle can be represented by an S-curve:

$$\mathrm{P(T)} = p + \frac{1}{m} Y(T) \tag{1}$$

P(T) the likelihood of purchase at T

T time

p the coefficient of innovation

q the coefficient of imitation

m the total number of purchasing

$Y(T)$ number of previous purchasers.

Mahajan et al. (1990) grouped the employers into five categories, including the diffusion of innovation, and calculated the time when the employer categories were divided. T^* (maximum spread time) can be calculated as:

$$T^* = -\frac{1}{(p+q)} \ln\left(\frac{p}{q}\right) \tag{2}$$

Moreover, T_1 (early majority start time) and T_2 (late majority end time) can be calculated as

$$T_1 = -\frac{1}{(p+q)} \ln\left[\left(2+\sqrt{3}\right)\frac{p}{q}\right] \tag{3}$$

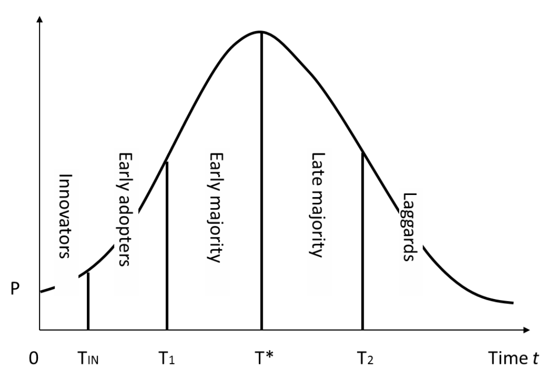
$$T_2 = -\frac{1}{(p+q)} \ln\left[\frac{1}{\left(2+\sqrt{3}\right)}\frac{p}{q}\right] \tag{4}$$

Furthermore, Yamada and Furukawa (1996) devised a formula for calculating T_{IN} (innovative hiring start time) as a division between the innovators and the early adopters.

$$T_{IN} = T^* - 2\left(T^* - T_1\right) = 2T_1 - T^* \tag{5}$$

Figure 1 exhibits the Bass innovation diffusion model based on equations (1) to (5).

Figure 1 The Bass innovation diffusion model ($0 < T_{IN}$)

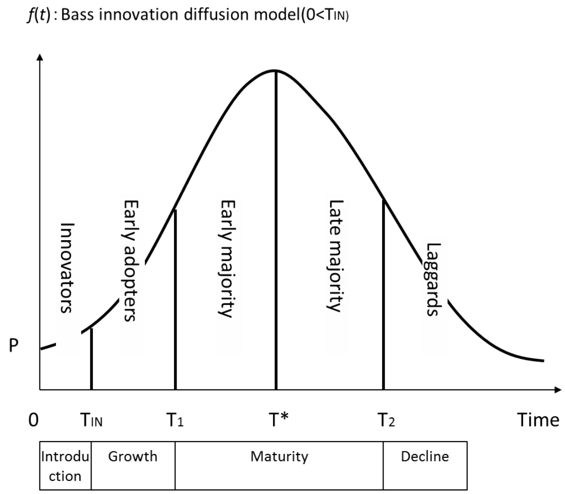


Source: Own elaboration

Kotler and Keller (2016) illustrated that customers of the introduction period in the product life cycle are the innovators; of growth are the early adopters; of maturity are the majority; and of decline are the laggards. Figure 2 depicts the combination with the Bass innovation diffusion model.

From Figure 2, it is evident that each period of the product life cycle can be quantitatively classified, and customers in each period can also be defined. Nonetheless, the Bass innovation diffusion model does not relate each period to product characteristics.

Figure 2 Combination with the bass innovation diffusion model



Source: Own elaboration

2.4 *Product life cycle and transition of customer needs*

Akabane (2016) specified five basic elements of customer needs: function, performance, design, brand, and price, which have the following relationship with the product life cycle. In the introduction and growth periods, it is necessary to focus on functions and performance. When technology plateaus, it becomes difficult to differentiate in terms of function and performance, deeming it necessary to differentiate by design in the mature stage. Furthermore, as commoditisation progresses, prices will form a means of appeal. From maturity to decline, it is likely that alternative products/successors will be introduced. Customers flow to them naturally and under such circumstances, it is imperative to appeal to customers and create a strong brand. Figure 3 displays the product life cycle and changes in customer needs.

Previous research has been able to relate the product life cycle with product characteristics, which was not possible with the Bass innovation diffusion model. Nevertheless, no quantitative analysis has been performed. The relationship is solely based on the nature of each product characteristic.

2.5 *Limitations of the literature reviewed*

The limitations of previous research are organised from the standpoints of 'discovery of information that leads to the emergence of innovation' and 'effective information when considering product life cycle'.

Figure 3 Product life cycle and changes in customer needs (see online version for colours)

		Product life cycle			
		Introduction	Growth	Maturity	Decline
	Functionality needs				
	Performance needs				
Customer needs	Design needs				
	Brand needs				
	Price needs				

Source: Own elaboration based on Akabane (2016)

2.5.1 Discovery of information and emergence of innovation

The analysis of product brands, categories, or characteristics can be categorised into two types: hedonic and utilitarian benefits. However, it is difficult to classify product characteristics into only two factors because multiple factors are needed to classify them. Moreover, the relationship between the two types of value is independent and cannot be analysed in an integrated manner.

2.5.2 Valid information

Function, performance, design, brand, and price are cited as basic elements that constitute customer needs, and the relationship between the product life cycle and product characteristics is qualitatively defined using the characteristics of these elements. Moreover, the product life cycle and product characteristics cannot be quantitatively associated.

Section 3 proposes research questions and hypotheses based on the limitations of previous research.

3 Research questions and hypotheses

3.1 Research questions

This study investigated the following research questions: 'Is it possible to extract information that leads to the emergence of innovation using statistical processing on the information associated with the product?' and 'Is the extracted information used when considering the product life cycle valid?'

3.2 Hypotheses

Swan et al. (2005, pp.144–164) identified four components of robust product design: 'functionality', 'aesthetics', 'operability', and 'quality'. Homburg et al. (2015) defined product design as a multidimensional concept consisting of the following three dimensions: aesthetics, functionality, and symbolism.

Here, a contradiction arises. Design is classified as a hedonic benefit, while functionality and quality that are the prime components of a design are classified as utilitarian benefits. Therefore, it is difficult to express value (i.e., product characteristics) in two dimensions as previously done; instead, it must be expressed in multiple dimensions.

Parasuraman (1997) and Johnson et al. (2006) argued that value is a dynamic concept, that is, the one likely to change over time. They also pointed out that the attributes that customers use to determine value can change over time as well. The product life cycle is the axis that captures time. Kotler and Keller (2006) found that the strategies implemented need to be changed depending on the period of the product life cycle. Based on the above, Hypotheses 1 and 2 are proposed as follows.

Hypothesis 1 Products can be classified based on the benefits of 'product functions' and can be expressed in multiple dimensions.

Hypothesis 2 Product characteristics change over time, in patterns, which can be explained in the product life cycle.

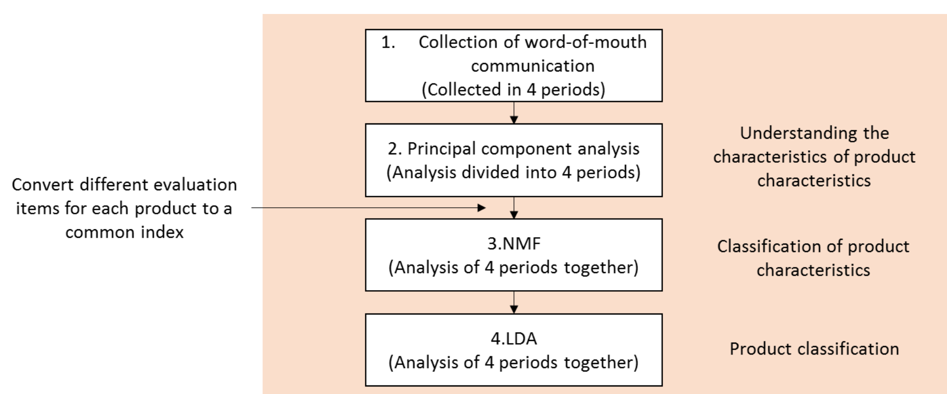
4 Methodology

4.1 Methodology 1

The purpose of this research was to 'classify product characteristics into multiple dimensions' and 'classify products based on its results'.

Principal component analysis, non-negative matrix factorisation (NMF), a clustering method, and LDA, a probabilistic model, was conducted based on a word-of-mouth website analysed across four periods. This analysis helps comprehend a product's characteristics. By performing the NMF based on the results of principal component analysis, product characteristics can be grouped into multiple dimensions. Products can also be classified by conducting an LDA based on the results of the NMF. Figure 4 describes the proposed method of methodology 1.

Figure 4 The proposed method of methodology 1 (see online version for colours)



Source: Own elaboration

Initially, we collected data through word-of-mouth communication across four periods. Since the product life cycle consists of introduction, growth, maturity, and decline, these four periods was used accordingly. Principal component analysis was conducted to understand the characteristics of the product. Based on the works of Chitturi et al. (2008) and Holbrook et al. (1982), benefits can be broadly classified into two categories. Therefore, in the principal component analysis, the first and second principal components were targeted. Table 1 depicts an example of the results of principal component analysis. The first and second principal components can be explained by all variables, and portability, respectively.

Table 1 Example of the results of principal component analysis

	PC1	*PC2*
Design	–0.638	0.44
Image quality	–0.678	–0.211
Operability	–0.762	–0.088
Battery	–0.621	–0.245
Portability	–0.555	0.701
Functionality	–0.78	–0.07
Liquid crystal	–0.745	–0.1
Sense of hold	–0.713	–0.251

Source: Own elaboration

Table 2 Defined common indicators

Related/not related to the number of features	Related/not related to the level of function	Related/not related to the speed/speed of function
Related/not related to appearance (design)	Related/not related to touch	Related/not related to reliability (less maintenance/ease/stable operation)
Related/not related to durability	Related/not related to operability (input from the operator)	Related/not related to operability (feedback to the operator)
Related/not related to the number of choices	Related/not related to dealing with various environments	Related/not related to resource-saving
Related/not related to space-saving	Related/not related to the environment	Related/ not related to safety
Related/not related to portability	Related/not related to the practicality of the function	Related/not related to after-sales service (not the product itself)
Related/not related to comfort (operating sound)		

Source: Own elaboration

Since the product characteristics of word-of-mouth websites vary with product, there is no common index to analyse and compare them. Therefore, a common index was created with reference to Garvin (1987), who proposed eight quality factors: performance, features, reliability, conformance, durability, serviceability, aesthetics, and perceived quality. Since Garvin's index does not cover all product characteristics, we redefined it to avoid omissions with a smaller granularity that enabled us to analyse influencing factors and classify products without using a priori product classification. As a result, 19 indicators emerged.

In this study, 19 indicators were defined. Table 2 presents the defined common indicators. This proposed method determines which index the evaluation item of the word-of-mouth site is classified into. For instance, in the case of a digital camera, the product characteristics are ‘image quality’ and ‘design’. ‘Image quality’ is classified as ‘related/not related to the level of function’. ‘Design’ is ‘related/not related to appearance (design)’. Subsequently, after converting the product characteristics into a common index, the appearance frequency of the product characteristics is counted. An example of the result is shown in Table 3. The result is the original data of the NMF.

Afterwards, the NMF was executed for every main component to classify product characteristics. The LDA was performed for each main component using the NMF results as input data for product grouping. When performing the NMF, the number of bases must be determined by the analyst. As only one method determines the number of bases, it should be changed one by one, and a viable candidate resides wherein the reduction range of the distance error becomes small.

Table 3 Example of the results of NMF

	Digital camera
Related/not related to the number of features	
Related/not related to the level of function	3
Related/not related to the speed/speed of function	
Related/not related to appearance (design)	1
Related/not related to touch	1
Related/not related to durability	
Related/not related to operability (input from the operator)	1
Related/not related to operability (feedback to the operator)	1

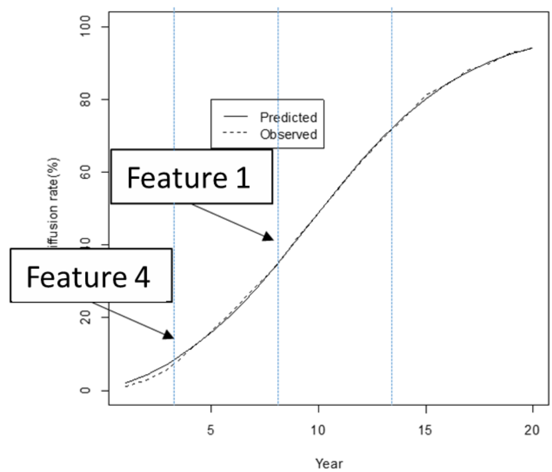
Source: Own elaboration

4.2 Methodology 2

This research aimed to clarify the change in product characteristics and the relationship between the changes in product characteristics and life cycle. The results of methodology 1 revealed which products are categorised into which topics at what time. We examined the relationship between the changes in the product characteristics and life cycle using the topic and high co-occurrence features. Simultaneously, the Bass innovation diffusion model was applied to quantitatively classify the product life cycle. The penetration rate for each year was calculated from the actual number of total shipments to Japan from 1999 to 2018. The diffusion rate and coefficients of innovation and imitation were used as input values for the Bass model. The initial values of the coefficients of innovation and imitation were determined randomly based on comparable products. Till 2002, no breakdown was observed; 2003 onwards, a breakdown of integrated and interchangeable lens type and SLR cameras was observed; 2012 onwards, a breakdown of integrated, interchangeable lens type, SLR cameras, and non-flex cameras (mirrorless, compact cameras, etc.) was observed.

Table 4 exemplifies the results of methodology 1 whereby the characteristics have high co-occurrence with each topic. For example, feature 4 has high co-occurrence with topic 2, and feature 1 has high co-occurrence with topic 4. Combined with the results of the Bass innovation diffusion model, important characteristics can be derived for each period. Figure 5 illustrates an example of the results of the relationship between the Bass innovation diffusion model and its features.

Figure 5 Example of the results of the relationship between the bass innovation diffusion model and the features (see online version for colours)



Source: Own elaboration

Table 4 Results of methodology 1 whereby the characteristics have high co-occurrence with each topic

	2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Product A	Topic 2	Topic 4	Topic 4	Topic 2

Source: Own elaboration

5 Results

5.1 Methodology 1

5.1.1 Analysis target of methodology 1

Methodology 1 grouped the product characteristics by combining word-of-mouth information (i.e., evaluation scores of product characteristics) with the principal component analysis, NMF, LDA, and product life cycle.

We relied on the evaluation score of Kakaku.com, which is a word-of-mouth website regarding home appliances. Kakaku.com has a total of 460.72 million monthly page views and 64.21 million monthly users (as of June 2021). It is the largest word-of-mouth website for home appliances in Japan and includes an overall satisfaction score, evaluation scores for product characteristics, and word-of-mouth reviews. Other sites (e.g., Amazon.com and Shopping.com) list the average overall satisfaction score of products, but not the satisfaction score of each product unit. Therefore, analysis from the perspective of product functions is unachievable.

Kakaku.com has been posting reviews since December 2005. The period covered by word-of-mouth communication was from December 2005 to April 2020 (i.e., some products are available until June 2020). Separate reviews were conducted for 2005–2008, 2009–2012, 2013–2016, and 2017–2020. Kakaku.com has about 800 categories with the smallest number of reviews being less than ten. The largest category has about 48,000 reviews. Owing to the large variation in the number of reviews, this study focussed on analysing 103 products and the categories with more than 1,000 reviews. Reviews with no ratings were excluded. Table 5 exhibits an example of a representative product.

Table 5 Example of a representative product

Large category	*Medium category*	*Number of products*	*An example of the product*
Camera	Camera accessories	6	Lens, Tripod_Monopod
	Camera body	3	Digital single-lens reflex camera
	Flash memory	2	SD memory card, compact flash
Smartphones/mobile phones	Smartphones/mobile phones	5	Au, DoCoMo, Softbank
PC	PC software	1	Security software
	PC parts	14	CPU, memory
	PC peripherals	17	Printer, projector
	PC body	5	Desktop PCs, laptops
Home appliances	AV/information appliances	22	Blu-ray player, speaker
	Seasonal home appliances	5	Humidifier, dehumidifier
	Health/beauty appliances	9	Massager, shaver
	Cooking/household appliances	13	Washing machine, toaster
Car	Car supplies	1	Car navigation

Note: [1]Au, DoCoMo, and Softbank are Japanese mobile carriers.

Source: Own elaboration

5.1.2 Results of methodology 1

In all the results, the cumulative contribution rate reached approximately 50%–90% for the second main component. The number of principal components was two. The results of the principal component analysis for lenses from 2005 to 2008 are outlined and exemplified in Tables 6 and 7.

The principal component load is the correlation coefficient between the original variable and the principal component. The ideal target is when the absolute value of the principal component load is 0.5 or more. If it is less than 0.5, it can be assessed that there was no correlation; thus, it is considered that there was no significant effect even upon exclusion. Based on the results of the principal component analysis, product characteristics (i.e., operability, expressiveness, portability, and functionality) were converted into common indicators. Table 8 presents the results of conversion derived from the correspondence between the product characteristics of each product and common index.

Table 6 Results of the principal component analysis for lenses from 2005 to 2008 part 1

	PC1	*PC2*
Standard deviation	1.51	0.89
Proportion of variance	0.57	0.20
Cumulative contribution rate	0.57	0.77

Source: Own elaboration

Table 7 Results of the principal component analysis for lenses from 2005 to 2008 part 2

	PC1	*PC2*
Operability	0.82	–0.00
Expressiveness	0.75	–0.36
Portability	0.59	0.78
Functionality	0.83	–0.23

Source: Own elaboration

Table 8 Results of conversion derived from the correspondence between the product characteristics of each product and the common index

	PC1	*PC2*
Operability	Operability (input)	
Expressiveness	Level of function	
Portability	Portability	Portability
Functionality	Level of function	

Source: Own elaboration

Table 9 Number of bases of the first principal component and the transition of the error

Base	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
Root mean square residual	0.41	0.36	0.32	0.29	0.26	0.24	0.22	0.20	0.20	0.15	
Error		0.05	0.04	0.03	0.03	0.02	0.02	0.02	0	0.05	0.15

Source: Own elaboration

Table 10 Number of bases of the second principal component and the transition of the error

Base	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
Root mean square residual	0.21	0.18	0.16	0.13	0.11	0.10	0.09	0.07	0.06	0.05	
Error		0.03	0.02	0.03	0.02	0.01	0.01	0.02	0.01	0.01	0.05

Source: Own elaboration

This process was conducted for each product across each period. The principal component analysis helps decipher a product's characteristics.

Next is the determination of the number of bases. Table 9 indicates the number of bases of the first principal component and transition of the error, whereas Table 10 shows the number of bases of the second principal component and transition of the error.

Table 11 Results of NMF performed on the first principal component

Feature 1	Number of features	Level of function	Appearance	Touch	Space saving
Feature 2	Level of function	Appearance	Operability (input)	Space saving	Comfort
Feature 3	Appearance	Operability (input)	Operability (feedback)	Number of choices	Portability
Feature 4	Speed of function	Appearance	Durability	After-sales service	Comfort
Feature 5	Number of features	Appearance	Reliability	Number of choices	After-sales service

Source: Own elaboration

Table 12 Results of NMF conducted on the second principal component

Feature 1	Number of features	Speed of function	Appearance	Number of choices	Portability
Feature 2	Number of features	Level of function	Speed of function	Number of choices	Practicality of the function
Feature 3	Number of features	Reliability	Resource saving	Space saving	After-sales service
Feature 4	Reliability	Durability	Operability (input)	Portability	After-sales service
Feature 5	Number of features	Speed of function	Reliability	Durability	Comfort
Feature 6	Touch	Reliability	Number of choices	Resource saving	After-sales service
Feature 7	Number of features	Speed of function	Reliability	Resource saving	After-sales service

Source: Own elaboration

Table 13 Representative results of the top five topic models based on the co-occurrence of topics and products ‘first principal component’ ‘topic 1’

Product	*Probability of appearance*
2013–2016 DoCoMo	0.011
2017–2020 LCD TVs	0.009
2005–2008 Keyboard	0.008
2013–2016 PC monitor_LCD display	0.007
2005–2008 Softbank	0.007

Source: Own elaboration

Table 14 Representative results of the top five topic models based on the co-occurrence of topics and products 'first principal component' 'topic 2'

Product	*Probability of appearance*
2005–2008 au	0.009
2013–2016 Blu-ray_DVD recorder	0.009
2005–2008 CDplayer	0.007
2005–2008 Plasma TV	0.007
2009–2012 Home bakery	0.007

Source: Own elaboration

Table 15 Representative results of the top five topic models based on the co-occurrence of topics and products 'first principal component' 'topic 3'

Product	*Probability of appearance*
2005–2008 Loudspeaker	0.010
2009–2012 au	0.007
2005–2008 Massager	0.007
2017–2020 Tablet PC	0.007
2017–2020 Air conditioner_Cooler	0.007

Source: Own elaboration

Table 16 Representative results of the top five topic models based on the co-occurrence of topics and products 'first principal component' 'topic 4'

Product	*Probability of appearance*
2005–2008 tablet PCs	0.009
2009–2012 laptops	0.008
2017–2020 DVD player	0.007
2009–2012 plasma TV	0.007
2005–2008 IC recorder	0.007

Source: Own elaboration

Table 17 Representative results of the top five topic models based on the co-occurrence of topics and products 'first principal component' 'topic 5'

Product	*Probability of appearance*
2009–2012 IC recorder	0.008
2009–2012 PC monitor_LCD display	0.007
2005–2008 Mac	0.007
2017–2020 Hard disk case	0.007
2005–2008 Vacuum cleaner	0.007

Source: Own elaboration

In the case of the first and second principal components, a base of five and seven was determined, respectively. To simplify the analysis, the number of features was arranged according to the top five listings. Tables 11 and 12 present the results of the NMF conducted on the first and second principal components, respectively.

Next, Tables 13–24 present the representative results of the top five topic models based on the co-occurrence of topics and products. In the case of the first principal component, topic 1 is as shown in Tables 13–17. In the case of the second, topic 1 is as shown in Tables 18–24. We were able to classify each product using the LDA. Tables 25 and 26 highlight the findings of the topic model based on the co-occurrence of topics and features.

Table 18 Representative results of the top five topic models based on the co-occurrence of topics and products 'second principal component' 'topic 1'

Product	*Probability of appearance*
2005–2008 Digital audio player	0.026
2017–2020 Motherboard	0.024
2013–2016 Motherboard	0.024
2009–2012 Motherboard	0.024
2005–2008 Motherboard	0.024

Source: Own elaboration

Table 19 Representative results of the top five topic models based on the co-occurrence of topics and products 'second principal component' 'topic 2'

Product	*Probability of appearance*
2009–2012 case fan	0.050
2013–2016 case fan	0.050
2005–2008 case fan	0.038
2009–2012 HDD 3.5 inch	0.020
2013–2016 HDD 3.5 inch	0.020

Source: Own elaboration

Table 20 Representative results of the top five topic models based on the co-occurrence of topics and products 'second principal component' 'topic 3'

Product	*Probability of appearance*
2005–2008 PC speaker	0.009
2005–2008 Printer	0.009
2005–2008 DVD player	0.009
2005–2008 Soundbar	0.009
2005–2008 Radio	0.009

Source: Own elaboration

Table 21 Representative results of the top five topic models based on the co-occurrence of topics and products 'second principal component' 'topic 4'

Product	*Probability of appearance*
2009–2012 Soundbar	0.010
2017–2020 PC case	0.010
2005–2008 Hard disk case	0.005
2005–2008 PC monitor_LCD display	0.005
2005–2008 USB memory	0.005

Source: Own elaboration

Table 22 Representative results of the top five topic models based on the co-occurrence of topics and products 'second principal component' 'topic 5'

Product	*Probability of appearance*
2005–2008 tablet PCs	0.026
2013–2016 Softbank	0.025
2009–2012 tripod monopod	0.022
2013–2016 tablet PCs	0.014
2013–2016 Card reader	0.014

Source: Own elaboration

Table 23 Representative results of the top five topic models based on the co-occurrence of topics and products 'second principal component' 'topic 6'

Product	*Probability of appearance*
2005–2008 Conversion lens_Adapter	0.060
2017–2020 tripod monopod	0.045
2009–2012 Sound card_Unit	0.034
2009–2012 Compact flash	0.031
2013–2016 tripod monopod	0.031

Source: Own elaboration

Table 24 Representative results of the top five topic models based on the co-occurrence of topics and products 'second principal component' 'topic 7'

Product	*Probability of appearance*
2009–2012 Digital audio player	0.025
2005–2008 Earphones_Headphones	0.017
2005–2008 Blu-ray_DVD recorder	0.017
2009–2012 Car navigation	0.017
2013–2016 Earphones_Headphones	0.017

Source: Own elaboration

Table 25 Findings of the topic model based on the co-occurrence of topics and features 'first principal component'

Topic	*Feature*	*Gamma*
1	1	0.201
2	4	0.200
3	3	0.201
4	1	0.202
5	4	0.205

Source: Own elaboration

5.2. Methodology 2

5.2.1 Analysis target of methodology 2

As an example, the Bass innovation popularisation model was applied to digital cameras, LCD/plasma TVs, car navigation, and air conditioner/cooler.

Table 26 Findings of the topic model based on the co-occurrence of topics and features 'second principal component'

Topic	*Feature*	*Gamma*
1	6	0.998
2	2	0.700
3	2	0.299
4	1	0.999
5	3	0.999
6	4	0.999
7	5	0.998

Source: Own elaboration

5.2.2 Results of methodology 2

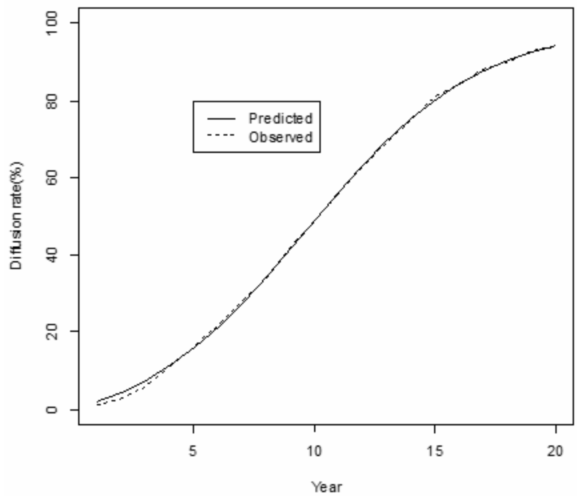
The Bass model is used to quantitatively classify a product life cycle (i.e., introduction, growth, maturity, and decline). Table 27 displays the results of quantitative classification of the life cycle of each product. The results of applying the Bass model of the digital camera are shown in Figure 6.

Table 27 Results of quantitative classification of the life cycle of each product

	Introduction	*Growth*	*Maturity*	*Decline*
Digital camera			2004–2012	2013–
LCD TVs/plasma TVs		–2006	2007–2010	2011–
Car navigation			2007–2022	
Air conditioner/cooler				1992–

Source: Own elaboration

Figure 6 Results of applying the bass model of the digital camera



Source: Own elaboration

- p: 0.02, q: 0.26, m: 99.68
- Range that contains the p-value < 0.001

Source: Camera & Imaging Products Association

In case of LCD TVs/plasma TVs:

- p: 0.05, q: 0.54, m: 99.18
- Range that contains the p-value < 0.001

Source: Consumer Confidence Survey, Cabinet Office

In case of car navigation:

- p: 0.01, q: 0.14, m: 101.00
- Range that contains the p-value < 0.001

Source: Japan Electronics and Information Technology Industries Association

In case of air conditioner/cooler:

- p: 0.00, q: 0.14, m: 91.11
- Range that contains the p-value < 0.001

Source: Consumer Confidence Survey, Cabinet Office

Next, using the product characteristics and the Bass innovation diffusion model, the results of the relationship between the product characteristics and product life cycle are illustrated in Tables 28 and 29.

In case of the digital camera in Table 28, the results of the first principal component indicate that the 'number of functions', 'level of functions', 'feel', and 'space-saving' are novel, appearing between 2013 and 2016. Next, in case of the digital camera in Table 29, the results of the second principal component indicate that the 'number of functions', 'reliability', 'resource-saving', 'space-saving', and 'after-sales service' appeared in all periods.

The results of applying the Bass model of the LCD/plasma TVs are shown in Figure 7. Next, using the product characteristics and Bass innovation diffusion model, the results of the relationship between the product characteristics and product life cycle are illustrated in Tables 30–33.

Table 28 Results of the relationship between the product characteristics and product life cycle 'first principal component'

2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Maturity	Maturity	Decline	Decline
Feature 4	Feature 4	Feature 1	Feature 1
Speed of function	Speed of function		
Appearance	Appearance	Appearance	Appearance
Durability	Durability		
After-sales service	After-sales service		
Comfort	Comfort		
		Number of functions	Number of functions
		Level of functions	Level of functions
		Feel	Feel
		Space-saving	Space-saving

Source: Own elaboration

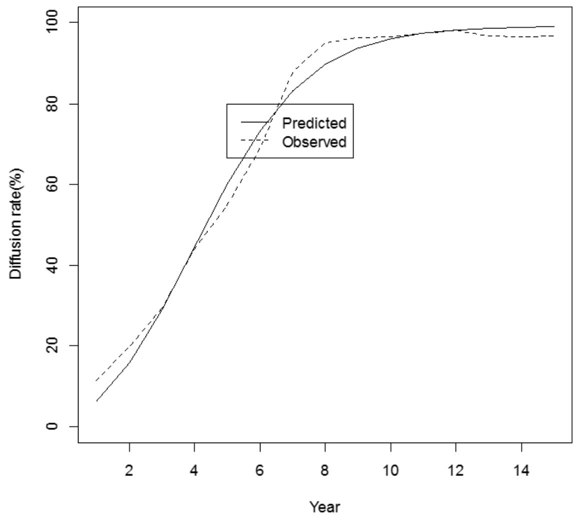
Table 29 Results of the relationship between the product characteristics and product life cycle 'second principal component'

2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Maturity	Maturity	Decline	Decline
Feature 3	Feature 3	Feature 3	Feature 3
Number of functions	Number of functions	Number of functions	Number of functions
Reliability	Reliability	Reliability	Reliability
Resource-saving	Resource-saving	Resource-saving	Resource-saving
Space-saving	Space-saving	Space-saving	Space-saving
After-sales service	After-sales service	After-sales service	After-sales service

Source: Own elaboration

In case of the LCD TVs in Table 30, the results of the first principal component indicate that the 'number of functions', 'level of functions', 'feel', and 'space-saving' are novel and appeared between 2009 and 2012. Next, in case of LCD TVs in Table 31, the results of the second principal component indicate that the 'number of functions', 'speed of function', 'reliability', 'durability', and 'comfort' appeared between 2005 and 2016. Next, 'level of function', 'number of choices', and 'practicality of the functions' appeared between 2017 and 2020.

Figure 7 Results of applying the bass model of the LCD TVs/plasma TVs



Source: Own elaboration

Table 30 Results of the relationship between the product characteristics and product life cycle 'first principal component' 'LCD TVs'

2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Introduction, growth, maturity	Maturity, decline	Decline	Decline
Feature 4	Feature 1	Feature 1	Feature 4
Speed of function			Speed of function
Appearance	Appearance	Appearance	Appearance
Durability			Durability
After-sales service			After-sales service
Comfort			Comfort
	Number of functions	Number of functions	
	Level of functions	Level of functions	
	Feel	Feel	
	Space-saving	Space-saving	

Source: Own elaboration

In case of the plasma TVs in Table 32, the results of the first principal component indicate that the 'number of functions', 'level of functions', 'feel', and 'space-saving' are novel and appeared between 2009 and 2012. Furthermore, between 2017 and 2020, the results are the same as those between 2005 and 2008. However, there is a discrepancy between the time of purchase and word-of-mouth because the analysis of the word-of-mouth for products purchased nearly ten years ago was conducted in 2020. Next, in case of the plasma TVs shown in Table 33, the results of the second principal component indicate that the product characteristics did not exist from 2005 to 2008 and were all explained by the first principal component, from 2009 to 2012, 'number of functions', 'speed of function', 'reliability', 'durability', and 'comfort' appeared. In addition, from 2013 to 2016, an appearance of 'level of functions', 'number of choices', and 'practicality of functions' was observed, and from 2017 to 2020, the appearance of 'feel', 'resource saving', and 'after-sales service' was observed.

The results of applying the Bass model of car navigation are shown in Figure 8. Next, using the product characteristics and Bass innovation diffusion model, the results of the relationship between the product characteristics and product life cycle are illustrated in Tables 34 and 35.

Table 31 Results of the relationship between the product characteristics and product life cycle 'second principal component' 'LCD TVs'

2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Introduction, growth, maturity	Maturity, decline	Decline	Decline
Feature 5	Feature 5	Feature 5	Feature 2
Number of functions	Number of functions	Number of functions	Number of functions
Speed of function	Speed of function	Speed of function	Speed of function
Reliability	Reliability	Reliability	
Durability	Durability	Durability	
Comfort	Comfort	Comfort	
			Level of functions
			Number of choices
			Practicality of the function

Source: Own elaboration

Table 32 Results of the relationship between the product characteristics and product life cycle 'first principal component' 'plasma TV'

2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Introduction, growth, maturity	Maturity, decline	Decline	Decline
Feature 4	Feature 1	Feature 1	Feature 4
Speed of function			Speed of function
Appearance	Appearance	Appearance	Appearance
Durability			Durability
After-sales service			After-sales service
Comfort			Comfort
	Number of functions	Number of functions	
	Level of functions	Level of functions	
	Feel	Feel	
	Space-saving	Space-saving	

Source: Own elaboration

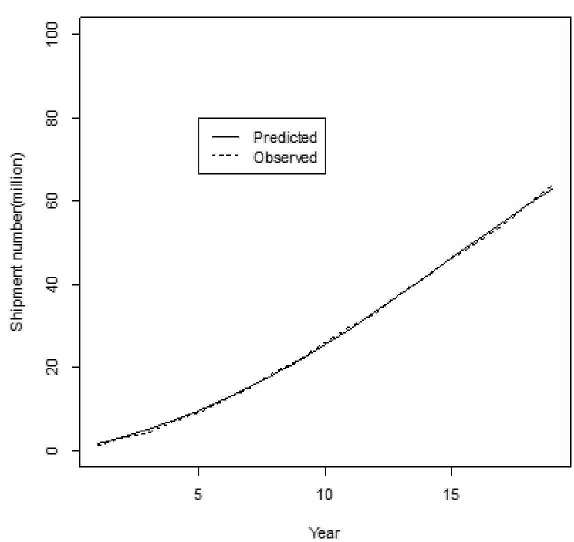
In case of the car navigation in Table 34, the results of the first principal component indicate that the 'speed of function', 'durability', 'after-sales service', and 'comfort' are novel and appeared between 2009 and 2012. In addition, the ‘number of functions’, ‘level of functions’, ‘feel’, and ‘space-saving’ appeared between 2013 and 2016. In the case of car navigation in Table 35, the results of the second principal component indicate that the ‘number of functions’, ‘speed of function’, ‘durability’, and ‘comfort’ appeared between 2009 and 2012. After 2013, no product characteristics existed, and the first principal component explained everything.

Table 33 Results of the relationship between the product characteristics and product life cycle ‘second principal component’ ‘plasma TV’

2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Introduction, growth, maturity	Maturity, decline	Decline	Decline
	Feature 5	Feature 2	Feature 6
	Number of functions	Number of functions	
	Speed of function	Speed of function	
	Reliability		Reliability
	Durability		
	Comfort		
		Level of functions	
		Number of choices	Number of choices
		Practicality of the function	
			Feel
			Resource saving
			After-sales service

Source: Own elaboration

Figure 8 Results of applying the bass model of the car navigation



Source: Own elaboration

The results of applying the Bass model of the air conditioner/cooler are shown in Figure 9. Using the product characteristics and Bass innovation diffusion model, the results of the relationship between the product characteristics and product life cycle are illustrated in Tables 36 and 37.

Table 34 Results of the relationship between the product characteristics and product life cycle 'first principal component'

2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Growth, maturity	Maturity	Maturity	Decline
Feature 3	Feature 4	Feature 1	Feature 1
Appearance	Appearance	Appearance	Appearance
Operability(input)			
Operability(feedback)			
Number of choices			
Portability			
	Speed of function		
	Durability		
	After-sales service		
	Comfort	Number of functions	Number of functions
		Level of functions	Level of functions
		Feel	Feel
		Space-saving	Space-saving

Source: Own elaboration

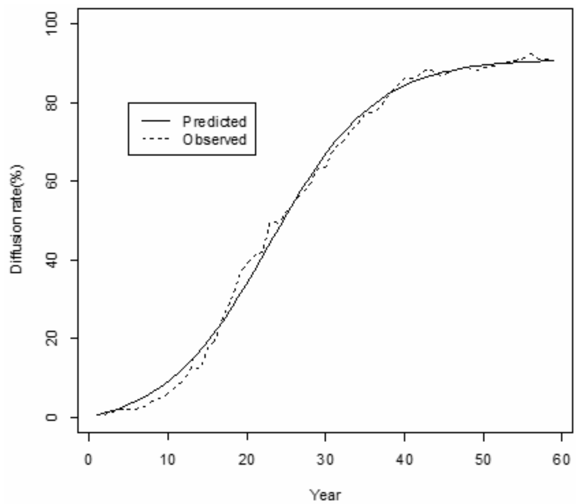
Table 35 Results of the relationship between the product characteristics and product life cycle 'second principal component'

2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Growth, maturity	Maturity	Maturity	Decline
Feature 6	Feature 5		
Touch			
Reliability	Reliability		
Number of choices			
Resource saving			
After-sales service			
	Number of functions		
	Speed of function		
	Durability		
	Comfort		

Source: Own elaboration

In case of the air conditioner/cooler in Table 36, the results of the first principal component indicate that the 'number of functions', 'level of functions', 'feel', and 'space-saving' are novel and appeared between 2009 and 2012. In addition, 'operability (input)’, ‘operability (feedback)’, ‘number of choices’, and ‘portability’ appeared between 2013 and 2016. In the case of the air conditioner/cooler in Table 37, the results of the second principal component indicated that the ‘number of functions’, ‘level of functions’, ‘speed of function’, ‘number of choices’, and ‘practicality of the function’ appeared from 2005 to 2016. Product characteristics do not exist between 2017 and 2020, and can all be explained by the first principal component.

Figure 9 Results of applying the bass model of the air conditioner/cooler



Source: Own elaboration

Table 36 Results of the relationship between the product characteristics and product life cycle ‘first principal component’

2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Decline	Decline	Decline	Decline
Feature 4	Feature 1	Feature 3	Feature 3
Speed of function			
Appearance		Appearance	Appearance
Durability			
After-sales service			
Comfort			
	Number of functions		
	Level of functions		
	Feel		
	Space-saving		
		Operability (input)	Operability (input)
		Operability (feedback)	Operability (feedback)
		Number of choices	Number of choices
		Portability	Portability

Source: Own elaboration

Table 37 Results of the relationship between the product characteristics and product life cycle 'second principal component'

2005–2008	*2009–2012*	*2013–2016*	*2017–2020*
Decline	Decline	Decline	Decline
Feature 2	Feature 2	Feature 2	
Number of functions	Number of functions	Number of functions	
Level of functions	Level of functions	Level of functions	
Speed of function	Speed of function	Speed of function	
Number of choices	Number of choices	Number of choices	
Practicality of the function	Practicality of the function	Practicality of the function	

Source: Own elaboration

6 Discussion

From the NMF results, a tendency can be inferred from the product characteristics included in each characteristic of the first principal component.

Feature 1 Features intended for home use (no sound).

Feature 2 Features intended for home use (things that produce sound).

Feature 3 Features that are supposed to be used outside.

Feature 4 Parts related/sound is produced.

Feature 5 Parts related.

Furthermore, from the NMF results, a tendency can be inferred from the product characteristics included in each characteristic of the second principal component.

Feature 1 Assuming outside use.

Feature 2 Assuming excessive quality.

Feature 3 Assuming cost performance (other than parts).

Feature 4 Assuming durability (outside).

Feature 5 Durability (home use, parts related).

Feature 6 Assuming to always touch.

Feature 7 Assuming cost performance (parts related).

From the LDA result, in the case of the first principal component (refer to Table 25), which is the topic model result, it co-occurs with feature 1; thus, topics 1 and 4 are similar. Similarly, topics 2 and 5 are identical because they co-occur with feature 4; however, topic 3 is not identical to any other topic.

In the case of the second principal component, the 2009–2012 case fan and 2005–2008 PC speaker are similar because they co-occur with feature 2. Moreover, the 2009–2012 tripod monopod is classified as topic 5, and the 2013–2016 tripod monopod is classified as topic 6. Different time series have different classified topics. Thus, it can be inferred that the characteristics have changed. Alternatively, both 2013–2016 and 2017–2020 tripod monopods are classified as topic 6, implying that the characteristics have not changed.

Notably, Holbrook et al. (1982) and Herzberg (1965) argued that value can be divided into utilitarian and hedonic benefits. In contrast, Swan et al. (2005, pp.144–164) proposed four components of robust product design: 'functionality', 'aesthetics', 'operability', and 'quality'. Furthermore, Okada (2005) stated that utilitarian and hedonic benefits are not necessarily at both ends of one dimension. Further, Okada (2005) signified that depending on the product/product characteristic, both utilitarian and hedonic benefits may be high or low. Hence, a product/product characteristic is not classified as having either utilitarian or hedonic benefits. According to the results of methodology 1, product characteristics can be classified into five components via the analysis of the first principal component and into seven components through the second principal component analysis. Likewise, while focussing on the appearance of the first principal component, it is noteworthy that appearance exists in all five groups. Therefore, the classification of the proposed method supports the claims of Swan et al. (2005) and Okada (2005).

The following is an integrated explanation considering previous studies. Cusumano (2008) validated that the iPod gained 70% market share not only because of its functionality and performance but also because of its unique 'Click Wheel' interface and new touch screen. In other words, it is thought that companies can develop high-performance and multifunctional products if they differentiate themselves through technology, but simultaneously, operability and ease of use are also required. According to the results of the proposed method, one product characteristic is classified into multiple groups, and the grouped result is not only the product characteristic related to function and performance but also the product characteristic related to features other than function and performance, such as design and operability. These findings suggest that utilitarian and hedonic benefits are not independent of each other and need to be examined in an integrated manner.

The following is an explanation from a methodological standpoint. In the case of product classification, a questionnaire survey was conducted using the SD method for product brands and product categories; and based on the results; factor analysis was used to quantitatively organise the products. It can be divided into two categories: utilitarian and hedonic benefits. Practical and emotional contents, such as 'useful/useless' and 'pleasant/unpleasant', are set as indicators of the SD method. However, Kakaku.com classifies products based on usage scenes. There are large home appliances, followed by medium ones, such as seasonal home appliances (including humidifiers, fans, and circulators) and health/beauty home appliances. Moreover, seasonal home appliances include products such as humidifiers, fans, and circulators.

Methodology 1 uses information from word-of-mouth websites instead of the SD method, which reduces the time and effort required to collect the questionnaires. The index uses product characteristics. Additionally, the classification is based not on practical and emotional characteristics but on the benefit of product characteristics. Moreover, one product characteristic is not classified into a solitary group, but into multiple groups. Consequently, one group has a mix of utilitarian and hedonic benefits in relation to product characteristics. Chronologically, technology and design have not been treated independently. The results of this study can provide a new perspective and lead to the emergence of innovation.

Regarding the relationship between product characteristics and the product life cycle, product characteristics fluctuated during their transition to maturity and decline. We can infer that the reason for the changing product characteristics is that the market had altered significantly.

Looking at the second principal component, the proposed method reveals product characteristics (prominent product characteristics) that could not be summarised by the first principal component. When the second principal component does not exist, the product is a general-purpose product, and when product characteristics exist in the second principal component, we can conclude that the product has outstanding characteristics.

The following similarities with previous studies were observed. The Bass innovation diffusion model was applied to digital cameras, and the result was an S-curve. Moreover, the Bass model, which is the basis of the Bass innovation diffusion model, estimates the diffusion curve with three variables – market size, innovator coefficient, and imitator coefficient – and does not use variables such as price and advertisement. Although only three variables were used, statistically significant values could be estimated, and, consequently, both the Bass model and the Bass innovation diffusion model were dependable.

The following differences from previous studies are noteworthy. Akabane (2016) highlighted that function and performance are vital during introduction and growth, and design and brand are critical during maturity and decline. In the results of the maturity and decline of the first principal component concerning digital cameras, the product characteristics related to function and performance, such as the number of functions and the level of functions, were important. Therefore, the result of this study is different from that of Akabane (2016). Customers do not always prioritise features and performance over design and brand. From the beginning, customers may be looking for design and brand as well as functionality and performance. The results suggest that concurrent development is also necessary, rather than focusing solely on functionality and performance.

There are two strategies for when a market enters a decline phase: first, withdrawal from the market, and second, innovation that will revitalise the market. Shintaku (1994) called the latter phenomenon de-maturity. When de-maturity occurs, the technological system becomes fluid again, and product innovation becomes active. In that case, product characteristics related to function and performance become imperative. Specifically, Abernathy and Utterback (1985) proposed three reasons for de-maturity: emergence of innovative technologies, changes in consumer demand, and changes in government policy. As a result of the maturity and decline of digital cameras, which are the first principal component, product characteristics related to functions and performance were deemed significant, and the diffusion of smartphones has made smartphones sufficient and consumer demand intricate. Therefore, we can deduce that the product characteristics related to function and performance have become important again.

The following is an explanation from a methodological perspective. Previously, only proposals for the Bass innovation diffusion model were made. Alternatively, by analysing past cases of companies and digging into the nature of product characteristics, previous research qualitatively linked each period of the product life cycle with innovation and product strategies. Furthermore, because of qualitative relations, for example, in introduction/growth, function and performance are important, and in maturity/decline, design and brand are important. Thus, no comprehensive analysis has been done.

Methodology 2 quantitatively defined each phase of the product life cycle using the Bass innovation diffusion model. Then, by combining the results of methodology 1, the relationship between each period of the product life cycle and the product characteristics was quantitatively analysed. It is possible to quantitatively verify whether it is correct. Moreover, since the results of methodology 1 are employed, the product characteristics are grouped from a comprehensive perspective. Therefore, the proposed method provides a new perspective that did not exist before, and this information can lead to the generation of innovation.

In this research, two hypotheses were established and evaluated to examine the research questions.

Hypothesis 1 stated that 'products can be classified based on the benefits of 'product functions' and this classification can be expressed in multiple dimensions'. The principal component analysis and NMF were performed on the evaluation points of product characteristics. In addition, the LDA was conducted based on the classification of product characteristics' results.

While classifying product characteristics, when the first principal component was targeted, the product characteristics could be classified into five components; when the second principal component was targeted, the product characteristics could be classified into seven components, and the product characteristics were quantitative. Moreover, the product characteristic was expressed in multiple dimensions. In terms of product classification, 2013–2016 DoCoMo and 2017–2020 LCD TVs could be classified in the same group. Further, the 2005–2008 tablet PCs and 2009–2012 laptops could be categorised in the same group. Since the four products have common product characteristics, they are comparable products even if they were classified into distinct groups.

Unlike methodology 2, this analysis considers the passage of time by dividing the duration from 2005 to 2020 into four periods. When classifying product characteristics, new classification criteria were defined, and products were classified based on those criteria, which uses a different classification perspective compared to before; thus, hypothesis 1 was supported.

Hypothesis 2 stated that 'product characteristics change with the passage of time, patterns exist in the changes, and the patterns can be explained in the product life cycle'. Using the Bass innovation diffusion model, this study quantitatively related product characteristics and the product life cycle.

In the case of digital cameras, product characteristics have changed over time. Product characteristics change when major alterations in customer needs occur. In recent years, it has become natural to post photos and videos to social networking services (SNS), and smartphones are becoming a viable alternative product. As product characteristics change, so does the period of the product life cycle. Therefore, Hypothesis 2 was supported.

With the support of the two hypotheses, it is possible that when classifying product characteristics, a new classification standard can be defined and products can be classified from a different viewpoint, which was previously not possible. As it is a new perspective, it is information that leads to the emergence of innovation. When new product characteristics appear over time, we can infer that there has been a major change in the market and that point of change can be inferred as the turning point of the product life cycle, which is effective when considering this life cycle. Accordingly, the research questions were answered.

7 Conclusions

7.1 Academic implications

First, the conventional research on value has pointed out that value can be divided into utilitarian and hedonic benefits, and the product/product characteristics have been classified as 'useful/useless' and 'pleasant/unpleasant' through questionnaire surveys. Quantitative analysis has been conducted based on the results. Subsequently, many product/product characteristics have been classified as either utilitarian or hedonic benefits, and both are independent of each other. However, some results can be aggregated into one or classified into three. Additionally, 'functionality', 'aesthetics', 'operability', and 'quality' are listed as components of a robust product design. Products/product characteristics cannot always be divided into two types. A benefit may consist of multiple product characteristics. In methodology 1, product characteristics were quantitatively grouped based on the evaluation points of product characteristics. Thereby, the product characteristics could be divided into five or seven groups. Moreover, one product characteristic was sorted into not one but multiple groups. Consequently, the values of both utilitarian and hedonic benefits are mixed within the group; hence, they need to be considered in an integrated manner rather than independently. Furthermore, the products could be classified quantitatively based on the results of the grouped product characteristics. Therefore, it is necessary to re-examine the discussions that can be expressed in two or three dimensions.

Second, in the conventional research on the product life cycle and product characteristics, each of their periods are qualitatively related to the research of past cases and the nature of product characteristics. Additionally, decisions are made within a predetermined framework. For instance, if function and performance are important, it is estimated to be in the introduction/growth. Nonetheless, product characteristics are not independent relationships, but multiple combination relationships, and need to be considered in an integrated manner. In methodology 2, the Bass innovation diffusion model and the results of methodology 1 were integrated to quantitatively relate each period of the product life cycle to the product characteristics. It is an evidence-based result. When the importance of product characteristics changes over time, it is possible to estimate the point of change in the product life cycle and its period. There are multifarious product patterns, wherein some products necessitate function and performance at the beginning, and others emphasise function and design at the beginning. By applying methodology 2, it is possible to estimate the change point of the product life cycle and the period of the product life cycle of various products. In the future, when analysing the relationship (i.e., innovation strategy, marketing method) with each period of a product life cycle, it will be necessary to perform a quantitative analysis.

Third, the conventional analysis of word-of-mouth is influenced by the restrictions of word-of-mouth websites (i.e., category classification and evaluation items), and the target products/services are limited. Accordingly, it was difficult to generalise the results. For example, only restaurants in New York and hotels in the Canary Islands were targeted, and cross-category analysis was not possible. Methodology 1 defines a common index; thus, it is not affected by the restrictions of word-of-mouth websites. It is possible to analyse not only across categories but also across word-of-mouth websites. Therefore, the generalisation of research results can be expected.

7.2 Practical implications

First, analysts can reduce costs because of open data and the simplicity of the method. It is easy for anyone to use.

Second, the proposed method can be used for product development. Previously, notebook and desktop PCs were classified in the same category as PCs. This study revealed that products classified into distinct categories are similar in terms of product characteristics. The technology used can be diverted and new functions may be introduced. Alternatively, the manufacturing process can be standardised, which may lead to cost reduction. In this way, information that leads to the emergence of innovation can be discovered.

Third, the proposed method was able to discover information that would lead to the emergence of innovation from the vast amount of information that humans cannot process. In addition, the proposed method was able to discover insight-providing information based on the results of data analysis and external theories. Bi et al. (2019) used the LDA for word-of-mouth information to find product characteristics that contribute to customer satisfaction. In the case of smartphones, Bi et al. (2019) found 18 product characteristics such as battery, camera, and LCD. In the case of digital cameras, Bi et al. (2019) found eight product characteristics such as price, operability, and image quality. Furthermore, by applying the Kano model, they visualised whether the found product characteristics are classified into attractive quality, one-dimensional quality, must-be quality, or reverse quality (Kano et al., 1984). Deeper insights can be gained by using external theories. Moreover, humans decide based on the results of data analysis. Machines and humans can be separated, and the proposed method can be a complement to humans.

7.3 Limitations and future works

First, accuracy cannot be measured. Precision and recall need to adapt.

Second, this study targeted word-of-mouth websites as an example. Thus, it is necessary to verify whether it can be applied to other fields and whether it derives information that leads to the emergence of innovation.

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