Using natural language analysis of product reviews to detect features contributing to life cycle price decline

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Abstract

As product life cycles become shorter, rates of price decline are accelerating. This study examined online reviews and used natural language processing and multiple regression analyses to identify the determinants that influence the rate of price decline in digital cameras. The coefficients for the external factors of portability, lens, and video were significantly positive, and the coefficients for battery, hold feel, underwater, and correction were significantly negative. Our proposed methodology can be employed for differentiation and product development strategies. Design, which has attracted attention in recent years in the context of value creation, did not affect the rate of price decline, suggesting that a full-scale re-examination of differentiation and product development strategies is imperative. This approach can be applied to product and marketing strategies.

Key words

hedonic approach, quantitative analysis, price rate, word-of-mouth communication, product strategy, natural language processing

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Introduction

Product life cycles are becoming ever shorter due to rapid changes in customer and market needs, technological innovation, and product obsolescence. It is common for companies to determine product prices that are comparable to or better than competitors when the product is in the mature stage of its life cycle. The price of the product then begins to decline, leading manufacturers to attempt to prolong the life cycle through efforts such as branding and differentiation strategies, to strengthen the protection of intellectual property rights. Products are differentiated by function, performance, appearance, and quality. Successful differentiation can maintain a higher price and prolong the product's life cycle. Data and digital technology can be used to analyse how to prolong a product's life cycle since phenomenal increases in the amount of open data available enable data analysis techniques that can more appropriately decipher complex situations.

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Historically, data were collected from individual retail stores, and it was difficult to collect them in large quantities. Today, there are numerous online review sites where consumers generate and gather product information. Therefore, retailers need to target online review sites to gather information that will help them prolong the life cycles of their products.

Current research focuses on how to quantitatively estimate prices based on objective indicators, such as product characteristics and performance. These measurements can lead to an understanding of how product characteristics can contribute to price setting and product differentiation points upon market introduction. However, differentiation points can change depending on market conditions; accurately ascertaining these changes remains difficult at this point in time. Difficulties include collecting information regarding the rate of a product's price decline (information not posted on review sites); without this, we cannot determine which characteristics contribute to the decline. Data collection problems include small sample sizes and the lack of important non-objective indicators; analysis is usually based on objective indicators, and since these are predetermined by the company, such indicators are difficult to obtain. These factors make it difficult to identify differentiation points, which vary with market conditions. As a result, it may not be possible to prolong a product's life cycle and utilise it for the next model, and it is impossible to formulate suitable product strategies.

In this study, we examined the factors that impact the rate of price decline by using statistical processing and natural language analysis of our collected quantitative data. The remainder of this paper proceeds as follows. Section 1 provides a literature review. Section 2 describes the research questions and hypotheses. Section 3 describes the materials and methodology employed in this study; and Sections 4 and 5 explain the findings of this study and present the discussion, respectively.

1. Literature review

We will first look at price decisions when bringing a new product or service to market. Next, we will discuss some of the characteristics of online markets, especially price dispersion. Finally, we will look at studies that use the hedonic approach.

"Skimming pricing" refers to setting a high selling price at the time of market introduction. This price is set in order to secure initial profit at the product introduction stage. Thereafter, as other companies follow suit and competitive advantage fades, the price gradually adjusts to limit a decline in sales. Penetration strategy is the pricing of new products or services to encourage early market penetration. Zhang and Chiang (2020a) found that it is optimal for myopic sellers to adopt a skimming pricing strategy, but for forward-looking sellers, either a skimming pricing strategy or a penetration strategy is optimal, depending on the potential market and consumer reference price effects.

Bambauer-Sachse and Grewal (2011), Kleinsasser and Wagner (2011), and Lewis (2015) conducted studies on fractional prices. Aalto-Setälä and Halonen (2004) and Manning and Sprott (2009) conducted studies to explain the role of integer prices. Schindler (2006), Levy et al., (2011), and Macé (2012) conducted studies that focused on prices ending in the number 9. Kumagai and Nagasawa (2019) consider the luxury strategy to be an effective anti-commoditisation tactic, as luxury brands appear to gain a sustainable competitive advantage, and brand differentiation can be achieved by adhering to the luxury strategy. Kalyanaram and Winer (1995) found that when the current market price is higher than the reference price, customers perceive a loss and are therefore less likely to purchase the product, decreasing demand. Conversely, they also found that when the current market price is lower than the reference price, customers perceive a gain and are more likely to purchase the product, further stimulating market demand. Chen and Chen (2017) showed that personalised pricing strategies may increase price competition, while return-guarantee schemes may reduce price competition and improve profits.

Price cuts occur when there is an imbalance between supply and demand. This is especially true when the buyer's position is strong. Simon (2015) proposed reasons for price wars such as over-capacity, commodity product, low growth, and industry structure.

Next, we discuss the characteristics of online marketplaces. According to Gorodnichenko et al., (2018), in the case of online marketplaces, there are price comparison websites that allow consumers to easily compare prices, which increases price competition and ultimately leads to lower price dispersion. Furthermore, suppliers do not have to change their price tags, so they do not incur the cost of price changes. Compared to the offline market, price dispersion in the online market can be expected to be small. Also, Cavallo (2018) noted that the frequency of price changes in the offline market has increased due to the influence of the online market.

Deltas et al., (2006) conducted an analysis on the price of PCs and their associated features, finding that the implicit price of quality decreases as new technology matures. Haynes et al., (2008) examined the relationship between sellers' pricing behaviour on price comparison sites and the market structure for digital cameras. They found that there is a strong negative relationship between the number of sellers and the price of digital cameras. Gorodnichenko et al., (2021) investigated the relationship between product quality and pricing of CPUs. They found that the speed of technological change in the CPU market is related to price declines.

Several studies have been conducted utilising the hedonic approach to price estimation. After estimating a market price function with land prices and housing prices as objective variables, environmental conditions are assessed through their parameters as explanatory variables. According to Hidano (1997), the formula is as follows:

$$\rho = \alpha_0 + \alpha_1 z_1 + \cdot \cdot \cdot + \alpha_i z_i + \varepsilon$$

ρ: land price, z: environmental conditions, ε: error term, α: parameter

Galarraga et al., (2011) used the hedonic method after aggregating data for the refrigerator market in Spain's Basque region to identify the price premium for the most energy-efficient refrigerators. Explanatory variables included energy efficiency, capacity, whether or not the refrigerator was wall-mountable, the presence of a defrost function, colours available other than white, and brand. The findings revealed that refrigerators with higher energy efficiency were 8.9% more expensive. Moreover, larger refrigerators tended to be more expensive, as were those with a defrost function, which were 8.9% more expensive. Additionally, refrigerators in colours other than white were 19% more expensive, and wall-mounted refrigerators had a price premium of 14.5% over non-integrated refrigerators.

Ahmad et al., (2019) estimated the prices of mobile phones based on their attributes via a hedonic pricing model. The results specified that brand, battery capacity, weight, operating system, random access memory (RAM), memory size, and display size had significantly positive effects on a cell phone's price. The authors found that manufacturers need to develop strategies that concentrate on battery capacity of 2000-3000 mAH (milliampere-hour), RAM of at least 1GB (gigabyte), screen size of at least five inches, memory size of at least 8GB, back camera of at least 15MP (megapixel), 4G (fourth-generation wireless) network mode, a front camera, and FM (frequency modulation) radio.

Zhang and Wenwen (2020b) used a hedonic pricing model to observe the impact of attributes of refrigerators (i.e. policy, product, and platform attributes) on prices. The target data were collected from JD.com, an e-commerce website in China. The policy attribute refers to government regulations for refrigerators, the product attribute refers to product functions and parameters, and the platform attribute refers to JD.com. The research concluded that brand, energy efficiency, subsidy, purchasing index, control model, cooling mode, refrigeration type, volume, and the number of doors, among others, had a significant impact on price.

The above results show that the hedonic approach can be applied to a wide range of subjects. The common denominator in these studies is the use of static information as explanatory variables. Specifically, price is set as the objective variable, and the explanatory variables include the set product specifications.

2. Methodology

Our research question and hypotheses address the limitations of previous studies.

RQ: Can information from online review sites, natural language processing, and statistical processing be used to identify factors contributing to price decline over a product's life cycle?

According to Kotler (2011), the pricing strategy for the product life cycle is as follows: during the introduction period, prices tend to be higher due to higher manufacturing costs. During the growth phase, prices remain the same or decrease slightly. In the mature stage, prices are frequently reduced. In the period of decline, price cuts are expanded. However, according to Chung et al. (2015), new products are expected to appear in the declining phase. Therefore, the effect of price reduction will eventually be lost.

Hypothesis 1: The maturity period of the product life cycle contributes to price decline.

Suzuki et al. (2019) stated that value consists of utilitarian benefits and hedonic benefits.[1] As commoditisation progresses, hedonic benefits become more important.

Hypothesis 2: Hedonic benefits will contribute to price declines. Further, the tendency towards price decline is weak. Meanwhile, utilitarian benefits do not contribute to price decline.

Conventional analysis has used evaluation items such as word-of-mouth sites and product specifications, which are vague expressions, such as functionality and design. In addition, the evaluation items and specifications are arbitrary and determined by the companies. Barreda et al. (2013) conducted a textual analysis of hotel review site information. The results showed that the most important factors for hotel users were friendly staff, reservation, service provided, and courtesy. In addition, the actual evaluation items for word-of-mouth sites were "location," "cleanliness," "service," and "price."

Hypothesis 3: By analysing text information, it is possible to discover specific product characteristics that contribute to lower prices.

We used digital cameras as the target product since digital cameras in Japan are an important market with a large share of the global market. Because there has been an increase in the number of e-commerce sites, where product prices and reputation information are stored (e.g. Amazon and Tripadvisor), information on e-commerce sites is important to both companies and users, who make purchase decisions based on information pertaining to reputation. We gathered data from Kakau.com, a review site for consumer electronic products.

[1] Utilitarian benefits can be evaluated objectively and quantitatively. Hedonic benefits are evaluated subjectively and qualitatively by means of human judgment.

2.1. Rating items and satisfaction

This study used item rating and overall satisfaction to assess the relationship between determinants that affect the rate of price decline of products. According to Kotler (2011), the reasons for which companies implement price reductions include gaining an advantage over competitors and the imminent release of a new model. Thus, we used the product life cycle period and the successor model as variables. A multiple regression analysis was conducted (stepwise method) with price decline rate as the explained variable and predictor variables comprising design, image quality, operability, battery, portability, functionality, LCD, hold feel, overall satisfaction, product life cycle period, and successor model.

According to Gorodnichenko et al., (2021), the hedonic approach is a common approach to ensure correct pricing. Thus, in this study, we used the hedonic approach. However, the hedonic approach ignores the fact that correct pricing is also affected by other factors such as market characteristics. Therefore, this study used product life cycle (sales year) and the availability of successor models as market factors.

2.2. Natural language analysis

Natural language processing is a technology in which the language used by humans in everyday communication (natural language) is understood and processed by computers. This technology is used in areas such as machine translation (Google Translate), dialogue systems (Alexa, Siri), and text mining (SNS analysis, survey analysis, stock market forecasting).

According to Okumura (2010), natural language processing can be divided into four major steps: (1) morphological analysis, (2) syntactic analysis, (3) semantic analysis, and (4) contextual analysis. Using natural language processing, nouns and adjectives can be extracted and the frequency of their occurrence can be counted. In this study, this result is set as an explanatory variable. We conducted a multiple regression analysis on the quantitative text data using the most common 10 nouns and suffix nouns with the highest frequency of occurrence as explanatory variables and the price decline rate as the objective variable (stepwise method). According to Rodrigues and Chiplunkar (2016), product features are usually nouns, and opinions are usually adjectives. Natural language analysis extracts the features of a product from reviews. We focused on nouns, excluding proprietary nouns as these do not express product features. The findings confirmed that significant words which contribute to the price decline rate can be determined. Furthermore, by investigating the words that occur in association with significant words, it is possible to understand the contexts in which they are used.

3. Research results

3.1 Data

As mentioned above, we gathered data on digital cameras from Kakau.com. We used eight evaluation values: design, image quality, operability, battery, portability, functionality, liquid crystal, and hold feel. Additionally, we integrated the value of customer satisfaction. The values were rated on a five-point scale (1 being the lowest and 5 the highest). Price decline rate (that is, the rate of decline from the initial price to the current price) and text information were also incorporated. Products with a listed rate of price decline were targeted. The price decline rate was based on data from 22 February 2021. Altogether, 70 products were analysed, and the total number of samples was 2,807. Table 1 lists the digital camera evaluation items and the evaluation criteria[2].

[2] Suzuki et al., (2019) determined that utilitarian benefits are image quality, battery, portability, and functionality, while hedonic benefits are design, operability, liquid crystal, and hold feel.

Table 1. Evaluation items and evaluation criteria

Evaluation item	**Evaluation criteria**
Design	Good appearance, texture
Image quality	Fineness of image, less noise, etc.
Operability	Ease of menu operation and function setting
Battery	Positive response to battery presence
Portability	Lightness, compactness
Functionality	Image stabilisation, shooting mode, etc.
Liquid crystal	Viewing ease of LCD screen
Sense of hold	Possible to hold firmly

Source: own elaboration based on Kakaku.com

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

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

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

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 purchases
Y(T) : number of previous purchasers

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

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

Moreover, T1 (early majority start time) and T2 (late majority end time) can be calculated as:

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

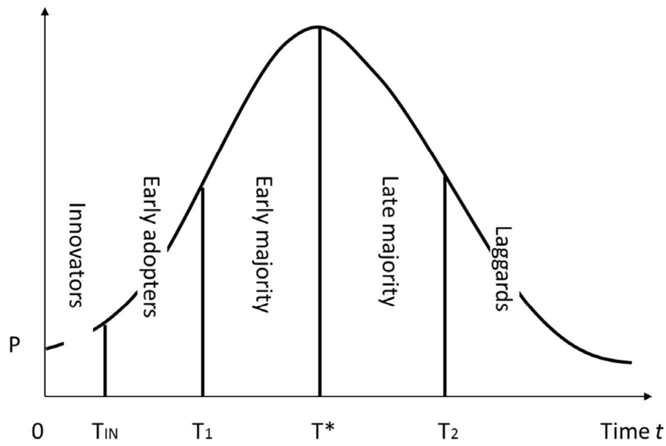
$$T_2 = -\frac{1}{(p+q)}\ln\left[\frac{1}{(2+\sqrt{3})}\frac{p}{q}\right] \ldots\ldots \ (4)$$

Furthermore, Yamada et al., (1995) devised a formula for calculating TIN (Innovative Hiring Start Time) as a differentiating between innovators and early adopters.

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

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

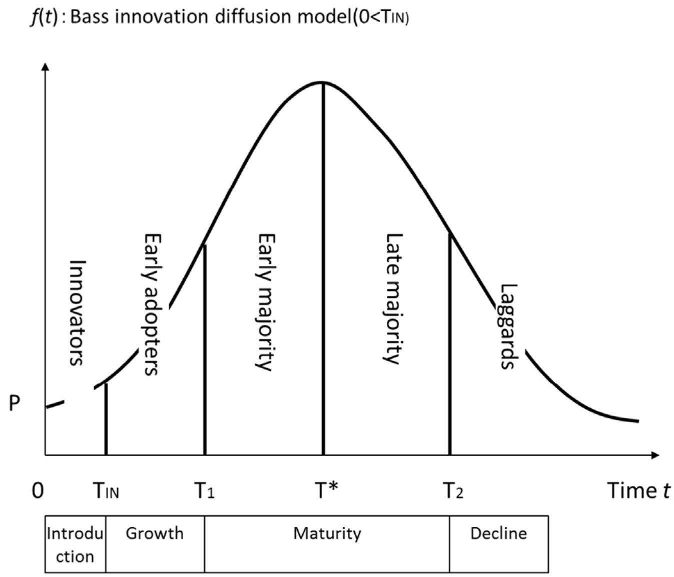
Figure 1. The Bass innovation diffusion model ($0<T_{IN}$)



Source: own elaboration based on Yamada, 1995

Kotler et al. (2015) illustrate that innovators are customers at the introduction stage of the product life cycle; early adopters are customers at the growth stage; the majority are customers at the maturity stage; and laggards are customers at the decline stage. Figure 2 depicts the combination with the Bass innovation diffusion model.

Figure 2. Combination with the Bass innovation diffusion model



Source: own elaboration based on Yamada, 1995

From the above figure, it is evident that each period of the product life cycle can be quantitatively classified, and customers in each period can also be defined.

The Bass model is used to quantitatively classify a product life cycle (i.e. introduction, growth, maturity, and decline). Table 2 displays the results of quantitative classification of the life cycle of each product.

Table 2. The results of quantitative classification of the life cycle of each product

	Introduction	Growth	Maturity	Decline
Digital camera			2004-2012	2013-

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

Source: own elaboration

Table 3 shows the results of the natural language analysis. The variance inflation factor (VIF) was less than 10, and there was no issue of multicollinearity.

Table 3. Results of rating items and satisfaction

Variable	**Coefficient**	**t-value**
Intercept	***21.197	18.864
Maturity	***17.744	45.795
Successor model	***5.672	3.511
Satisfaction	-0.385	-1.591
Operability	**0.671	2.769
Battery	-0.283	-1.466
Portability	***0.909	4.352
Sense of hold	***-1.099	-5.439
Adjusted R-squared	0.464	

***p < 0.001, *p < 0.05

Source: own elaboration

The explanatory variables were maturity, decline, successor model, satisfaction, design, image quality, operability, battery, portability, functionality, LCD, and hold feel. The stepwise method was used, and maturity, successor model, satisfaction, operability, battery, portability, and hold feel remained as a result.

Although the adjusted R-squared is not high (0.464), the coefficients of maturity, successor models, and portability are significantly positive (price-sensitive); therefore, careful interpretation is necessary. Since reasons for price erosion are difficult to determine, the coefficients for satisfaction, battery, and hold feel are significantly negative. External factors, such as products that have reached the mature period and products with successive models, are prone to price decline. The internal factors of operability and portability also indicate price decline. However, battery and hold feel, which are internal factors, are less prone to price decline. Satisfaction with the product as a whole is also unlikely to lead to price decline.

Hypothesis 1 states that the maturity period will contribute to price decline, and the results confirm this. In other words, prices are expected to decrease with the passage of time. When a successor model is sold, the price of the older model decreases. However, some users may not buy the old model even if the price drops because they want the new product. Operability, which is a hedonic benefit, is an item that contributes to the drop in price. Meanwhile, hold feel, which is also a pleasure benefit, does not tend to decrease the price. Portability, which is a functional benefit, also contributes to price decline, which is a different result from Hypothesis 2. Smartphones are rivals to digital cameras. In recent years, the image quality of smartphones has been improving, and they are simple to use. Functions that are not available on smartphones are considered important. Therefore, the relationship between hold feel and the downward trend in prices is considered to be weak.

Table 4 illustrates the results of the natural language analysis. The VIF is less than 10, and there was no issue of multicollinearity.

Table 4. Results of natural language analysis

Variable	Coefficient	t-value
Intercept	***11.055	8.128
Underwater	**-3.111	-3.365
Lens	***0.102	3.535
Direction	***43.345	6.772
Object	**2.513	3.091
Battery	0.773	1.938
Video	**0.183	2.826
Scoring	***0.918	6.166
Single-lens	**-0.111	-2.722
Use	-0.205	-1.478
Dial	**-1.940	-2.993
Correction	**-1.151	-3.253
Charging	**3.126	2.727
Hold	0.165	1.464
Workplace	**6.432	3.015
Liquid crystal	***0.137	4.524
Pixel	***1.722	5.399
Series	-0.740	-1.565
Wide-angle	0.552	1.714
Macro	0.685	1.395
Purchase	***0.056	4.314
Adjusted R-squared	0.719	

***p < 0.001, *p < 0.05

Source: own elaboration

47 nouns were extracted from word-of-mouth sites, and 20 nouns were selected by means of the stepwise method.

The adjusted R-squared value was high at 0.719. The coefficients for lens, direction, object, video, scoring, charging, workplace, pixels, and purchase were significantly positive (i.e. prone to price decline). By contrast, the coefficients of underwater, single-lens, dial, and correction were significantly negative (i.e. less prone to price decline). We found through text analysis that items that were expressed in terms of functionality on the word-of-mouth sites tend to use words that describe specific functions such as underwater, lens, video, and correction. Moreover, significant nouns facilitating the price decline rate can be extracted; here, we extract words that co-occur with such nouns to understand specific reasons. Table 5 illustrates the results of Word co-occurrence.

Table 5. Results of Word co-occurrence

Word	Word co-occurrence
Lens	Bright lens, Lens replacement, Telephoto lens, Focus lens
Direction	–
Object	Object blur, Moving objects
Video	Video shooting, 4K video, Video functions
Scoring	Scoring items, Self-scoring
Charging	USB charging, Charging time
Workplace	–
Pixel	Effective pixels, Pixel setting
Purchase	Pre-purchase, Additional purchase
Underwater	Underwater photography, Underwater housing
Single-lens	Single-lens reflex cameras, Mirrorless interchangeable-lens camera
Dial	Mode dial, Compensation dial, Dial operation
Correction	Shake correction, Exposure correction, Blur correction

Source: own elaboration

In the case of lenses, the words that co-occur are words such as bright lens. A bright lens is a lens that can take beautiful pictures even without sufficient light. Since it is not a feature found in smartphones, it contributes to price decline, but the coefficient is low. In the case of underwater, the words that co-occur include underwater housing. Since underwater housing (e.g. a waterproof case) is a high-quality feature that is not found in smartphones, it is differentiated. In sum, as proposed in Hypothesis 3, specific product characteristics can be discovered by analysing word-of-mouth communication.

4. Discussion

This study examined reputation information, such as evaluation scores, on online review sites and found that analyses of customer perspectives are possible. Furthermore, an analysis that considers external factors can be conducted via the addition of the product life cycle as an explanatory variable. The product life cycle period was a significant variable, suggesting that external factors are imperative when targeting durable consumer goods.

Conventional analysis using objective information may use items predetermined by the manufacturer, which can result in missing important items. In natural language analysis, explanatory variables are set based on the frequency of word occurrences in the reviews. This reduces the possibility of missing important items. In addition, word co-occurrence provides a deeper understanding of significant words. Our proposed methods can be adapted to products other than those reviewed on online sites, provided that textual information is available. When text-based analysis is used, it is easier to examine products' technological trends as they are introduced (e.g. 4K resolution).

Previous studies have estimated which items contribute to price, but not the items that contribute to the rate of price decline. Through natural language analysis, this study was able to identify the product characteristics that contribute to the rate of price decline. Deltas et al. (2006) and Gorodnichenko et al., (2021) pointed out that for CPUs and PCs, price decline is related to the speed of technological innovation. However, since it is unclear in which areas technological innovation took place, it is not clear which product features are related to price declines. For electronics products, there are few studies on the relationship between product features and price declines; Biyalogorsky et al., (2021) found that the price of a car declines with age, usage (mileage), and condition. They found that specific features contribute to the price. The method using the hedonic approach is similar, but it targets utilitarian benefits. In this study, hedonic benefits are also targeted. The results show that hold feel is a function with a weak tendency to decrease the price; integrating the studies of Deltas et al., (2006) and Gorodnichenko et al., (2021), we may observe that there is innovation or technological maturity in the field of hold feel. Baye et al., (2006), using product age as a dummy instead of product life cycle, showed that price dispersion decreases as product age increases. However, the relationship with product life cycle is unclear.

According to Eisenman (2013), in recent years, design has attracted attention as a product differentiator. Suzuki et al., (2019) conducted multiple regression analyses for digital cameras with customer satisfaction as the explained variable and the evaluation items as predictor variables. They discovered that operability and design contribute to customer satisfaction; however, design did not contribute to price decline. Hence, design is critical for satisfaction and initial pricing, but does not affect the rate of price decline. The results of this study also found that design does not contribute to price decline.

When analysing reputation information, it is better to target adjectives, but it is also possible to find significant nouns (i.e. words that describe product functions).

Conclusions

Significant evaluation items and words were distinguished through natural language analysis. By integrating natural language analysis and statistical processing of online reviews, the correlation between satisfaction, evaluation scores, external factors, and word occurrence frequency were analysed regarding the rate of price decline.

The results indicate which product attributes deserve focus for differentiation and product development strategies. The findings show that design, which has been attracting attention in recent years for value creation, does not affect the rate of price decline; this suggests that a full-scale re-examination of differentiation and product development strategies is required. Analysts can reduce the costs of obtaining data by using open data and natural language analysis with multiple regression. This methodology can uncover information leading to longer product life cycles, utilisation of the next product model, and strategic product strategy planning. In the future, the selection of different types of target words is recommended, such as adjectives and verbs.

McGrath (2001) points out that companies plan their development chronologically and conditionally (e.g. market environment, competitive landscape, and internal development resources) for each product. In this way, the product is introduced to the market at the right time, covers the company's targeted market segment, and ensures competitive advantage. However, the usual conventional analysis conducted at the point of market introduction fails to take the passage of time into account. By combining the conventional method (estimation of initial price) and the methodology presented in this study (estimation of rate of price decline), we can obtain a time-series and conditional (market environment) analysis.

According to Ogura and Tsuda (2018), e-commerce businesses change selling prices in response to market demand and supply. In order to differentiate their products from competing products and for quick inventory turnover, discount campaigns and point of sale (POS) order return are effective means of stimulating consumer demand. Additionally, when faced with the risk of unexpected inventory depletion, prices may be drastically reduced and liquidated at a loss. Hence, the analysis needs to take inventory and sales policies into account. No weighting is applied when extracting words; tf-idf can be used to extract characteristic words.

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