A computer-based approach for analyzing consumer demands in electronic word-of-mouth

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Abstract Consumer opinions are one of the most valuable assets that enterprises have, and thus questionnaires are often employed to investigate the views of consumers. However, this approach requires a large amount of human labor and time, and, most importantly, it cannot automatically find out consumers' needs. However, many consumers now share their appraisals of products or services through electronic word-of-mouth (eWOM). Since these usually reflect consumer needs, and thus their demands, collecting and analyzing eWOM data has become a key task for many businesses. Nonetheless, current eWOM-related research focuses on its transmission, influence, issues, and marketing, and there seem to be very few studies that apply eWOM to develop consumer needs analysis systems. In order to effectively collect and analyze eWOM data, this study proposes a computer-based approach for analyzing consumer demands. The approach utilizes sentiment analysis to develop extraction

methods for use with eWOM appraisals. It thus uses eWOM appraisals to find out consumer demands. This work integrates eWOM with information technology to develop an approach to computerize consumer needs analysis. It is expected that the results will help enterprises to improve the quality of their products and market competitiveness.

Keywords Electronic Word-of-Mouth (eWOM) · Knowledge management · Consumer demands · Sentiment analysis

JEL Classification C88 Other Computer Software

Introduction

In this service economy era, enterprises' primary goals include rapid responses to consumer requirements, shortening the time needed to launch new products or services, and improving the quality of their products (Choi et al. 2011; Chen and Cheng 2009; Walstad and Rebeck 2002). To meet these goals, more and more companies are putting efforts into discovering consumer demands with regard to their brands, products, and services. This information can then be used as a reference when designing new products or making innovations. Therefore, the efficient gathering and analysis of consumer demands can help companies to remain competitive (Kuo et al. 2009; Bei and Shang 2006; Chen et al. 2016).

With the development of new technologies, a growing number of consumers now post their opinions about products or services on blogs, web forums, and bulletin board systems (BBS), as well as in e-mails. This phenomenon is called, "electronic word-of-mouth" (eWOM) or "online word-of-mouth" (Hennig-Thurau and Walsh 2003, Pai et al. 2013a). eWOM is essentially consumer product or service appraisals, and thus also include important consumer demands. In order to

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understand consumer demands, enterprises are therefore investing a substantial amount of money in the collection and analysis of eWOM content. However, the tremendous amount of such information that is available online often overwhelms these collection and analysis efforts, and results in information overload (Park and Lee 2009).

A number of studies have undertaken examinations of the transmission (Chen et al. 2014; Erkan and Evans 2016), influence (Chu and Sung 2015; Kim and Johnson 2016; Wu and Lin 2017), and marketing (Nieto et al. 2014) of eWOM. Currently, however, there are very few eWOM-related studies that discuss the analysis of consumer demands through computerized eWOM. The most similar work to the current on is Archak et al. (2011), which defined the characteristics of a product and then brought up specific descriptions of the product from the eWOM content. The characteristics were then used to find consumers' needs. Appraisal words are the sentiments, opinions or thoughts consumers have toward products. As a result, Archak et al. (2011) used POS (part of speech) tagging to find out the nouns from the online appraisals, which were then used as the appraisal words. However, not every noun could express consumers' sentiments, opinions or thoughts. Besides, the analytical results of his research tended to be more subjective, because it required much labor used to cross reference the eWOM data, noun and appraisal words. Since most appraisals are done with sentiment words (Feng et al. 2011; Söderlund and Rosengren 2007), by applying emotion analysis techniques to eWOM, it is expected to that it will be possible to find the nouns related to sentiments. Instead of carrying out the analysis through traditional labor-intensive approaches, the current study applied many mature information technologies and method to do a consumer needs analysis using the eWOM data, nouns and appraisal words. Therefore, the analytical results of this study tend to be more objective. As such, this study is different from Archak et al. (2011) with regard to the data it analyzes.

By using appraisal words, it is expected that it will be possible to better understand consumers' preferences and get more comprehensive results. However, few studies have been conducted to investigate methods for the semantic analysis of eWOM. One of the advantages of analyzing eWOM content is that it directly reveals consumer opinions, which can enable enterprises to monitor market changes in real time. Nevertheless, the difficulty of analyzing eWOM lies in the complexity of the semantic content. Since consumers often use "text speak" to post their opinions online, and because there are no standard writing formats and unified descriptive words for online reviews (Pai et al. 2013a), the difficulty of analysis is increased. These problems also prevent computer programs from analyzing the text, and thus extracting the meanings of these terms is even more difficult. Despite the abovementioned difficulties, a number of enterprises continuously collect and analyze eWOM, aiming to find out consumer demands. Nevertheless, traditional eWOM data collection wastes a lot of time, which usually results in delayed

reactions to the market. Therefore, this study proposes a computer-based approach for the analysis of consumer demands. In order to develop a computerized eWOM analysis system, eWOM collection programs are employed to replace human labor in terms of searching and collecting eWOM content. The process of appraisal extraction and appraisal word classification is thus computerized to replace human labor. This use of information technology is expected to boost the speed of eWOM content analysis. In addition, traditional research into business administration or information technology puts emphasis on issues such as the spread, decision-making, and market-influence of eWOM. In contrast, information technology is rarely employed for the collection and analysis of eWOM. Therefore, employing information technology to analyze eWOM is an issue that deserves more attention. This study does not develop new algorithm or techniques for eWOM, but it applies well-developed information technology to develop a new application, and thus can be easily adopted by enterprises, and this indicated the value of the current work.

In summary, this study proposes a computer-based approach for the analysis of consumer demands. However, before constructing a complete system, a conceptual model or theory is suggested to be used as the foundation for developing it. As such, the system design is based on a review of the literature and is more reasonable than would otherwise be the case (Chen and Chen 2012; Chen 2011; Pai et al. 2013a; Pai et al. 2013b). Specifically, this study has the following objectives: (i) constructing a consumer demands analysis model in eWOM; (ii) designing a consumer demands analysis procedure; and (iii) developing a system for analyzing consumer demands. Finally, this study carries out an empirical test to validate the proposed method.

Consumer demands analysis model using eWOM

In order to analyze consumer demands efficiently, this section reviews traditional approaches for analyzing them and investigates the problems that they have. Approaches to the analysis of the relationship between appraisal words and consumer demands are also discussed. Finally, based on this review of the literature, details of the design of the consumer demand analysis model using eWOM are presented.

Review of traditional approaches for analyzing consumer demands

In order to gain the satisfaction and support of customers, businesses have long developed their products and services based on consumer opinions (Bai et al. 2008; Deng et al. 2010; Jiménez-Jiménez and Cegarra-Navarro 2007; Kim et al. 2004), with many enterprises and scholars using questionnaires to identify key consumer demands. The various methods that are used in the studies examined in this literature review to investigate consumer

Fig. 1 Traditional approaches for analyzing consumer demands

demands are shown in Fig. 1 (Kwon 2005; Grigoroudis and Siskos 2004; Park 2004), and described below.

Collection of evaluation factors Very often a researcher first collects the critical factors that influence purchasing decisions by employing two methods: First, experts are interviewed to identify evaluation factors. Second, a literature review is undertaken to identify evaluation factors. Nonetheless, these two data collection methods have their limitations. Insufficient information from the experts may jeopardize the reliability of the study, and an incomprehensive literature review can also hinder reliability.

Selection of evaluation factors After extensive data collection, the evaluation factors are organized and classified. This requires researchers to sort the data, and repetitions of similar evaluation factors are eliminated. However, this process is time-consuming and laborious.

Confirmation of consumer demand factors The generated evaluation factors are subsequently used to design a questionnaire. By this process, the exact consumer demand factors can be identified.

The procedures outlined above require a considerable amount of work to filter and organize the collected data. However, using a computer-based approach it is possible to use automation to reduce the complexity of this process and avoid errors, and thus improve the accuracy of consumer demands analysis.

Analysis of the relationship between appraisal words and consumer demands

To attain effective analysis of consumer demands from eWOM using computers, this research focuses on examining eWOM to gain insights. eWOM comes from consumers' actual encounters with the focal product or service, and includes valuable information on key consumer demands (Pai et al. 2013a). Consumers share their demands in eWOM using appraisal words when they have positive or negative experiences with a product or service. On the other hand, when the experience is not significantly good or bad, consumers tend not to use appraisal words to express their

demands. That said, in general appraisal word indicate consumer demands. Pai et al. (2013b) carried out a SWOT analysis on products or services by examining positive or negative appraisals. Enterprises can then use the results of the SWOT analysis to improve their products or services. SWOT is a tool for market analysis (Kotler and fox 1995), and this is done to better understand consumer needs and demands from the mass market. As a result, we can figure out consumer needs from eWOM appraisals (Pai et al. 2013b).

There are many studies that use keywords to obtain predictions of the economy or consumer decision-making. For example, Choi and Varian (2012) utilized Google Trends to carry out keyword analysis. The frequencies of the analysis were used as the near-term values of economic indicators. Moreover, Preis et al. (2013) found that the frequency of keywords could be used as "early warning signs". When a keyword is searched for more frequently, this may imply that it interests a lot of people. The frequencies of keywords can thus be used to assist investment decision-making. Similarly, when there are a lot of consumers who use a specific appraisal word to express their opinions about a product, the specific appraisal words used can present the needs and expectations of consumers. When the frequency of appraisal words rises or drops dramatically, then this can be seen as an early warning sign that businesses should pay attention to.

Generally speaking, the amount of appraisal a product or service receives tends to be steady, and a sudden shift in this would indicate a change in consumer demands. For example, certain aspects of a product would attract consumers' attention, thus leading to more appraisals, or another product's lack of features would not receive much interest, thus leading to a fall in the desire to discuss it. Therefore, when there is a significant change in the number of appraisals, it is likely that consumers' demands have altered. A company's marketing department and management could utilize this as a basis for determining consumer demands, and find out the reasons behind such changes. Statistically, the number of eWOM appraisal words is increasing every day. The sample of appraisal words collected in this study is $n \geq 30$, and thus a large sample pool. Based on central limit theorem, no matter what kind of distribution a population has, the sampling distribution approaches a normal one. Therefore, this

research assumes that eWOM appraisal words are normally distributed, and under a 95% confidence interval the frequencies of eWOM appraisal words would fall into the range of $[\mu + 2\sigma, \mu - 2\sigma]$. When the number of appraisal words exceeds the 95% confidence interval range, it means there is a significant change in the number of appraisals.

Frequencies have been used in many studies as an indicator of future trends. For instance, Google Trends uses the frequency of searches for keywords to determine trends in various related areas. Fig. 2 shows a progression graph for the keyword “KFC” (Kentucky Fried Chicken) between 2005 and 2010, and the letters A to M indicate different events during this period. As shown by the graph, the number of searches for KFC changes with each event, and this is especially true for events J and K. It could then be inferred that these two events attracted the most attention from consumers online. In this research, we focus on understanding consumer demands using appraisal words, and the consumers’ perceptions are shown by significant upswings or downswings in the use of these. In short, the frequencies of the appearance of appraisal words are used as indicators for identifying consumer demands.

Currently, many enterprises utilize eWOM to understand the competitive situations of their markets. They also use eWOM to understand the needs of consumers. Based on their understanding of consumer needs, enterprises can then take actions to cater to these, such as by making innovations or improving their products (Peter 1999). This also indicates that eWOM contains information about consumer needs. eWOM is thus an intellectual tool that is valued by enterprises, and many enterprises have started to collect and analyze eWOM to understand the needs of consumers. Therefore, we can view the appraisals or opinions of eWOM as consumer needs. A lot of appraisals related to products or services are expressed by using sentiment words (Söderlund and Rosengren 2007). Researchers such as Pai et al. (2013a) thus used sentiment analysis to extract information. The advantage of using information technology to process eWOM is that it can obtain eWOM-related information automatically. Businesses can then follow consumers’ opinions or appraisals and respond

to them more efficiently. Current information technology is able to collect and analyze eWOM automatically, so making it easier to understand consumer needs.

To effectively understand the relationship between appraisal words and consumer demands, we use one case for the purpose of demonstration. For example, eWOM authors use appraisal words, such as “delicious,” “smells good,” and “not bad,” to express their feelings about a food. However, eWOM authors’ use of such words varies due to their different demographic backgrounds, such as environment, education, and age. Different appraisal words from a variety of authors can cause difficulties in computerized content analysis. To clarify this information, appraisal words have been organized based on the following characteristics.

Synonyms These are appraisal words that describe similar consumer demand factors. For example, for the consumer demand factor “flavor,” “concentrated” is synonymous with “nice-smelling,” while for the consumer demand factor “environment,” “beautiful” is synonymous with “clean” (Fig. 3).

Antonyms Appraisal words that describe similar consumer demand factors but are opposite in meaning. For example, the appraisal words “nice-smelling” and “bad-smelling” express positive and negative flavor, respectively. Therefore, “nice-smelling” and “bad-smelling” are antonyms that describe the same consumer demand factor “flavor” (Fig. 4).

Multi-relational Appraisal words can sometimes be used to describe multiple consumer demand factors. For example, “not bad” and “very good” describe both the “flavor” and “environment” consumer demands factors.

The discussion above demonstrates that appraisal words encompass the concepts that consumers wish to express, which can represent key consumer demands. The present study classified appraisal words into categories based on their characteristics, as shown in Table 1.

Fig. 2 Keyword trends for “KFC”

Flavor	Environment
(Synonymous) -concentrated -nice-smelling -fragrant	(Synonymous) -beautiful -clean -comfortable

Fig. 3 Examples of synonymous appraisal words

Design of consumer demand analysis model in eWOM

Based on the analysis of the relationships between appraisal words and consumer demands, this study designed a consumer demands analysis model. This may help enterprises to have a better understanding of consumer demands, as shown in Fig. 5. In order to solidify the theoretical foundation of the consumer demands analysis model, this study applied the eWOM management framework for service experience (Pai et al. 2013a), and DIKW hierarchy (data, information, knowledge and wisdom hierarchy) (Rowley 2007) as the framework for designing the consumer demands analysis model. The consumer demands analysis model mainly consists of eWOM collection, appraisal extraction, and appraisal word classification, as is explained in more detail below:

eWOM collection eWOM belongs to the data level in DIKW hierarchy. The sources of eWOM were from blogs, web forums, and bulletin board systems (BBS). In order to effectively collect eWOM, this study used eWOM management framework for service experience (Pai et al. 2013a) as the framework. The consumer demands analysis model was used to design the eWOM collection stage, and the eWOM content was collected mainly from blogs, web forums, and bulletin board systems (BBS).

Appraisal extraction eWOM includes opinions and appraisal from consumers. The consumers often use appraisal words to express their opinions and thoughts. Therefore, the appraisals are important information for

eWOM data. This study applied the theory of DIKW hierarchy to extract these, with the appraisal words defined at the information level. In addition, we used the eWOM management framework for service experience (Pai et al. 2013a) to design the appraisal extraction stage in the consumer demands analysis model. The aim here is to find out important appraisal information from eWOM data.

Appraisal word classification Classification is a common tool that is often used in knowledge management. However, each appraisal word is an independent piece of information. In order to construct the relationships among appraisal words, we applied an appraisal classification to produce the knowledge context between appraisal words. Therefore, based on DIKW hierarchy theory, this study defined appraisal knowledge at the knowledge level. In order to solidify its theoretical foundations, this study used the eWOM management framework for service experience (Pai et al. 2013a). We designed the appraisal word classification stage in the consumer demands analysis model. The primary purpose of this is to classify and categorize appraisal words. After this, the knowledge context of appraisal words is produced.

Consumer demand identification Wisdom uses knowledge as its foundation. Through classifying, organizing, and analyzing this, new applications or values are found. Nonetheless, eWOM does not generate wisdom, but only business intelligence (BI). BI is a combination of statistics about business operations and analytical tools. It mainly provides information concerning market trends so that enterprises can carry out business planning or decision making (Watson and Wixom 2007). Hence, finding out consumer demands through eWOM can be said to be a kind of BI. BI and wisdom belong to advanced knowledge, that is, the wisdom level in the DIKW hierarchy. In order to solidify the theoretical foundation of the consumer demands analysis model, the researchers of this study referred to the eWOM management framework for service experience (Pai et al., 2013) in the designing consumer demand identification stage for the consumer demands analysis model. The primary function was to analyze appraisal knowledge so that the analytical results could serve as the basis to identify and filter consumer needs.

Flavor (Positive Appraisal)	Flavor (Negative Appraisal)
-concentrated -nice-smelling -fragrant	-diluted -bad-smelling -stinky

← Antonym →

Fig. 4 Examples of antonymous appraisal words

Methods and technologies

This study integrated the approaches shown in Fig. 5 into the design of procedure for analyzing consumer demands in eWOM. This procedure includes eWOM collection, appraisal extraction, appraisal word classification, and consumer demands identification.

Table 1 Definitions of appraisal word characteristics

Appraisal word characteristics	Definition	Classification
Synonyms	Appraisal words that describe similar consumer demand factors	Synonyms that describe the same consumer demand factor
Antonyms	Appraisal words that describe similar consumer demand factors, but are opposite in meaning	Antonyms that describe the same consumer demand factor
Multi-relational	Appraisal words that can be used to describe multiple consumer demand factors	Experts decide the classification of words

Procedure for analyzing consumer demands in eWOM

Based on the design of the consumer demands analysis model in eWOM in Fig. 5, this study develops procedures for consumer demands analysis. In this way, the enterprises may be able to better understand consumer demands, as shown in Fig. 6. The proposed consumer demands analysis in the eWOM procedure consists mainly of eWOM collection, appraisal extraction, appraisal word classification and consumer demands identification, as described in the sections that follow.

eWOM collection eWOM content is collected from the Internet with content collection and identification technologies, as follows:

- *Content collection*: The names of products, services, and companies are the keywords that are searched for in the web content.
- *eWOM identification*: The collected web content is filtered for appraisal words.

Appraisal extraction Semantic analysis and content extraction are conducted using the eWOM content to identify appraisal words related to the target products or services:

- *Parts of speech tagging*: All of the parts of speech in the text are identified.
- *Appraisal analysis*: Sentiment analysis technologies monitor unknown appraisal words.

Fig. 5 Consumer demands analysis model in eWOM

Fig. 6 The procedure for consumer demand analysis from eWOM

Appraisal word classification Appraisal words include consumer demands. Therefore, this study uses calculations of similarity to determine the relationships between appraisal words and consumer demands. The classifications for appraisal words are then used to calculate the frequencies of the appearance of appraisal words in consumer demand factors. The number of appearances are saved month-by-month.

Consumer demand identification By analyzing the frequencies of appraisal words in relation to consumer demand factors, consumer demand identification is conducted to identify changes in these demands.

eWOM collection

In order to effectively collect eWOM content, a collection method was developed to extract specific content related to eWOM communication and to exclude non-related content (Fig. 7). The eWOM collection processes mainly include “content collection” and “eWOM identification”, as described below:

Content collection To ensure efficient and accurate collection of related content (about specific products, services, or brands), the following processes and technologies were developed.

Fig. 7 eWOM collection process

Fig. 8 Automatic punctuation rules

- *Content crawler*: By searching web content using keywords (e.g., products, services, or brands), items of interest are extracted from blogs and online communities via the Google API (Application Programming Interface).
- *HTML structure analysis*: Each blog and online community has a unique HTML tag format. After obtaining the web content, the HTML structure is analyzed to facilitate extraction.
- *Automatic marking*: Web content is often presented in semi- or non-structured formats. Analyses of web content is generally hampered by the use of “text speak”, special symbols for certain online communities, a lack of punctuation, and other challenging characteristics. To address these problems, an automatic marking function is developed to analyze and categorize HTML language. This also punctuates the eWOM content with the aid of a rule database, thus improving the accuracy of the analysis of the parts of speech in Chinese texts (Fig. 8).
- *HTML tag refinement*: Tag refinement is primarily applied to eliminate advertisements and HTML language links, and thus only the important *parts* of the web content are retained, improving the efficiency of the follow-up procedures. This content is saved as a “*.txt” file.

eWOM identification The collected web content might still include information not related to eWOM communications.

The following filters are applied to extract only the required content.

- *Appraisal word filtering*: An appraisal word database is employed to locate web content that includes the appraisal words.
- *Content filtering*: Repeated content is deleted from the selected web content.

Appraisal extraction

Despite applying the above-mentioned filtering processes, the content still included some unidentified appraisal words. The following techniques were applied to determine the appraisal words that are commonly used by consumers, as shown in Fig. 9.

Fig. 9 Appraisal extraction process

Parts of speech tagging The Chinese Knowledge Information Processing (CKIP) system, developed by Academia Sinica in Taiwan, is used to tag parts of speech.

Appraisal analysis Consumer opinions have been frequently analyzed with sentiment analysis technologies (He and Zhou 2011; Fan and Chang 2010; Vechtomova 2010), and a variety of methods can be used with Chinese text. For instance, Pai et al. employed the Chinese sentiment analysis method proposed by Ku et al. (2005) to develop an eWOM analytical method (Pai et al. 2013a), further developing a SWOT analytical technique (Pai et al. 2013b) using the results of eWOM analysis. This work thus uses the analytical method in Pai et al. (2013a) and Ku et al. (2005) as the basis of appraisal analysis, with the following steps applied for analysis of unknown appraisal words.

First and foremost, this study conducted a calculation of the appraisal character weight, which indicates positive or negative values, as calculated with eqs. (1) and (2).

$$P_{ci} = \frac{fp_{ci}}{fp_{ci} + fn_{ci}} \quad (1)$$

$$N_{ci} = \frac{fn_{ci}}{fp_{ci} + fn_{ci}} \quad (2)$$

where ci is the i^{th} character in the appraisal character set, fp_{ci} is the number of times appraisal character ci appears in the positive appraisal word database; fn_{ci} is the number of times appraisal character ci appears in the negative appraisal word database; P_{ci} is the positive weight of the appraisal character ci , and N_{ci} is the negative weight of the appraisal character ci .

Equations (1) and (2) denote the number of times an appraisal character appears in the positive and negative appraisal word databases. Equations (3) and (4) regularize eqs. (1) and (2), respectively.

$$NP_{ci} = \frac{fp_{ci} / \sum_{j=1}^n fp_{cj}}{fp_{ci} / \sum_{j=1}^n fp_{cj} + fn_{ci} / \sum_{j=1}^m fn_{cj}} \quad (3)$$

$$NN_{ci} = 1 - NP_{ci} \quad (4)$$

where fp_{ci} is the number of times appraisal character ci appears in the positive appraisal word database; fn_{ci} is the number of times appraisal character ci appears in the negative appraisal word database; n is the total number of appraisal words in the positive appraisal word database, and m is the total number of appraisal words in the negative appraisal word database; NP_{ci} is the positive weight of appraisal character ci in the positive appraisal word database, and NN_{ci} is the negative weight of appraisal character ci in the negative appraisal word

database. The above-mentioned formulae are applied to weigh the appraisal characters, with the results shown in Table 2.

Based on these results, we carried out a calculation of appraisal word weight. In eq. (5), S_{cj} is the appraisal character weight of each appraisal character. NP_{ci} and NN_{ci} are the positive and negative weights of the appraisal characters, respectively, and are used to assess the meanings of these characters. For example, if NP_{ci} is greater than NN_{ci} , the appraisal character is positive, and vice versa.

$$S_{ci} = NP_{ci} - NN_{ci} \quad (5)$$

$$S_w = \frac{1}{p} \times \sum_{j=1}^p S_{cj} \quad (6)$$

Equation (6) primarily evaluates whether the appraisal word is positive or negative. S_w is the weight of the appraisal word, and is either positive or negative, p is the number of appraisal characters in the appraisal word, and S_{cj} is the appraisal character weight of each appraisal character. Table 3 gives the results of this process.

Appraisal word classification

Based on the analysis of the relationships between appraisal words and consumer demands carried out above, processes were designed to analyze the relationships between appraisal words and consumer demand factors by calculating the frequencies with which the appraisal words were found in consumer demand occurrences. This study analyzed the words with similar meanings in both appraisal words and consumer demand factors, with the results used as the basis for the categorization of the former. This study found the following 21 demand factors in a review of the literature: reliability, responsiveness, competence, access, courtesy, communication, credibility,

Table 2 Results of analyzing appraisal character weights

Appraisal character	Positive weight (NP_{ci})	Negative weight (NN_{ci})
安 (quiet or calm)	0.941,599,576	0.0512821
靜 (still or quiet)	0.905,542,268	0.0833333
藹 (friendly or gentle)	0.874,563,777	0.11,111,111
然 (but or just like that)	0.616,398,111	0.3,516,483
可 (approve)	0.558,651,364	0.4,077,669
親 (parents)	0.753,106,429	0.2,222,222
好 (good)	0.759,573,109	0.2,162,162
康 (healthy or abundant)	0.796,824,389	0.1,818,182

Table 3 Results of analyzing appraisal word weight

Appraisal word	Appraisal character weight (S_{ci})	Appraisal word weight (S_w)
安静 (peaceful)	安 (quiet or calm) = 0. 890,317,525 静 (still or quiet) = 0. 822,208,935	0. 85,626,323
好康 (good deal)	好 (good) = 0. 543,356,893 康 (healthy or abundant) = 0. 615,006,207	0. 57,918,155

security, understanding/knowing, tangibles, food quality, food price, food innovation, food rarity, natural food, food flavor, food mouthfeel, serving size, convenience of location, restaurant environment and restaurant style (Currie et al. 2009; Liu and Jang 2009; Ziethmal and Bitner 2003; French et al. 2000; Kivela et al. 1999; Earle 1997; Lee and Ulgado 1997). This study then constructed a database containing synonyms for all of these demand factors. There were two sources for this database. The first was the manual collection and classification of synonyms. The second was a comparison between the results of appraisal word classification and the synonyms database. Through this process, the synonyms that were not in the database were collected.

The Jaccard coefficient was applied to calculate the similarity between appraisal words and the synonym

corpus for the consumer demand factors. Their similarity was analyzed, and the results used as the basis for categorizing the appraisal words, using eq. (7).

$$\text{sim}(a_k, d_{ij}) = \frac{|a_k \cap d_{ij}|}{|a_k \cup d_{ij}|} \quad (7)$$

Based on eq. (7), the results of appraisal word classification are listed in Table 4. a_k is the appraisal word set, $a_k \in \{a_1, a_2, a_3, \dots, a_E\}$, and E indicates the number of appraisal word sets ($k = 1 \sim Z$). As for " d_{ij} ", i is the number of consumer demand factors, j is the ranking of the synonym in the corpus. This study uses appraisal word sets and the synonym corpus of consumer demand factors to construct a binary matrix, as shown in eq. (8).

$$\text{sim}(a_k, d_{ij}) = \begin{bmatrix} \text{Max}[\text{sim}(a_1, d_{1j})], & \text{Max}[\text{sim}(a_1, d_{2j})], & \dots, & \text{Max}[\text{sim}(a_1, d_{ij})] \\ \text{Max}[\text{sim}(a_2, d_{1j})], & \text{Max}[\text{sim}(a_2, d_{2j})], & \dots, & \text{Max}[\text{sim}(a_2, d_{ij})] \\ \dots\dots\dots & \dots\dots\dots & \ddots & \dots\dots\dots \\ \text{Max}[\text{sim}(a_k, d_{1j})], & \text{Max}[\text{sim}(a_k, d_{2j})], & \dots, & \text{Max}[\text{sim}(a_k, d_{ij})] \end{bmatrix} \quad (8)$$

In the binary matrix, $\text{sim}(a_k, d_{ij})$ indicates the similarity between the appraisal word set and consumer demand factors. If the value of similarity between appraisal words

and consumer demand factors is high, then the value of $\text{sim}(a_k, d_{ij})$ will almost be equal to 1, while the value of $r(a_m, b_n)$ will be near or equal to 0, as can be seen in Table 4.

Table 4 The similarity between the appraisal word set and consumer demand factors

CDF AW	d_{1j}	d_{2j}	d_{3j}	d_{4j}	d_{5j}	d_{6j}	d_{7j}	d_{8j}	...	d_{18j}	d_{19j}	d_{20j}	d_{21j}
a_1	0.000	0.943	0.000	0.000	0.000	0.218	0.142	0.333	...	0.142	0.000	0.000	0.000
a_2	0.000	0.139	1	0.189	0.427	0.000	0.000	0.000	...	0.086	0.478	0.776	0.000
a_3	1	0.000	0.000	0.000	0.000	0.219	0.000	0.142	...	0.147	0.499	0.200	0.000
a_4	0.000	0.652	1	0.000	0.053	0.000	0.208	0.189	...	0.000	0.037	0.707	0.000
a_5	0.152	0.153	0.000	0.635	1	0.196	0.000	0.000	...	0.000	0.000	0.000	0.000
a_6	0	1	0	0	0	0.0	0	0	...	0.153	0	0	0.142
a_7	0.000	0.000	0.460	0.189	0.905	0.443	0.000	1	...	0.362	0.000	0.111	0.000
a_8	0.000	0.000	0.783	0.382	0.000	0.381	0.000	0.154	...	0.000	0.383	1	0.000
a_9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	...	1	0.000	0.000	0.000
a_{10}	0.000	0.359	0.000	1	0.000	0.000	0.000	0.000	...	0.390	0.183	0.000	0.000

CDF: consumer demand factors; AW: appraisal word set.

In order to program the categorization of appraisal words, this study uses eq. 8 to design the algorithm for appraisal word classification, as shown in Table 5.

The frequencies at which consumer demands occur are saved through the method of appraisal word classification. As shown in Table 6, t_n indicates the number in each month,

Table 5 Algorithm of appraisal word classification

```

Algorithm appraisal word classification() {
  Input appraisal word set  $a_k$ 
  Input Consumer Demand Factors number  $m$ 
  double  $MaxSim = 0$ ,  $MaxOfSimArray = 0$ ,  $SimResult = 0$ ;
  int  $CDFIndex = 0$ ,  $I = 0$ ;
  double[]  $SimArray = \text{new double}[m]$ ;
  for  $a_k = a_1$  to  $a_E$  //  $a_k$  indicates appraisal word set,  $a_k \in \{a_1, a_2, a_3, \dots, a_E\}$  //
    for  $i = 1$  to  $m$  //  $i$  is the number of consumer demand factors. //
      for  $j = 1$  to  $n$  //  $j$  is the number of appraisal words. //
         $SimResult = \text{sim}(a_k, d_{ij})$ ; //  $SimResult$  is a temporary variable. It calculates the similarity between
        appraisal word  $a_k$  and consumer demand factors  $d_{ij}$ ,  $i$  is the consumer demand factors number,  $j$  is the order of
        appraisal words. //
        if ( $SimResult > MaxSim$ ) //  $SimResult$  is a temporary variable. It records the closest familiarity of
        appraisal word  $a_k$  in consumer demand factors  $d_{ij}$ . //
           $MaxSim = SimResult$ ; //  $MaxSim$  and  $SimResult$  is a temporary variable. It puts the value of
           $SimResult$  into  $MaxSim$ . //
        if-end
      for-end
       $SimArray[i - 1] = MaxSim$ ; //  $SimArray$  is a temporary variable. It uses  $SimArray$  to record the index
      value of appraisal  $a_k$  in  $MaxSim$ . //
       $MaxSim = 0$ ; // Sets the value of  $MaxSim$  as 0. //
    for-end
    for  $h = 0$  to  $SimArray.length - 1$  //  $h$  is a temporary variable. It records the length of data of  $SimArray$ .
     $SimArray.length$  is the command to calculate the length of  $SimArray$ . //
      if ( $SimArray[h] > MaxOfSimArray$ ) //  $SimArray$  is a temporary variable. It is used to find out the
      largest value of  $SimArray$ . //
         $MaxOfSimArray = SimArray[h]$ ; // It stores the largest value of  $SimArray$  array in
         $MaxOfSimArray$ . //
       $CDFIndex = h$ ; //  $CDFIndex$  is a temporary variable. It records  $SimArray$  the largest value of
       $SimArray$  array, index  $h$ .  $h$  is the order of consumer demand factors. //
    if-end
  for-end
   $I = CDFIndex + 1$  //  $I$  is a temporary variable.  $I$  is the number of consumer demand factors. //
   $a_k \in d_I$  // It categorizes appraisal word  $a_k$  into consumer demand factors  $d_I$ . //
for-end
}

```

Fig. 10 Estimation and confidence intervals

and ($t \in \{t_m, t = 1, 2, 3, \dots, n\}$), DF_1 to DF_{21} stand for consumer demand factors, including reliability, responsiveness, competence, access, courtesy, communication, credibility, security, understanding/ knowing, tangibles, food quality, food price, food innovation, food rarity, natural food, food flavor, food mouth feel, serving size, convenience of location, restaurant environment and restaurant style, respectively.

Consumer demands identification

Based on the results of appraisal word classification, the frequency with which appraisal words are found in consumer demand factors each month could be calculated. To translate

Table 6 The frequency of consumer demand occurrence

	t_1	t_2	t_3	t_4	t_5	t_6	...	...	...	t_n
DF_1	870	414	960	626	80	406	...	...	...	679
DF_2	954	12	339	828	989	45	...	...	...	293
DF_3	324	592	14	362	409	411	...	...	...	329
DF_4	745	780	564	874	559	19	...	...	...	911
DF_5	144	683	49	507	349	601	...	...	...	338
DF_6	416	241	734	62	653	773	...	...	...	256
DF_7	510	148	46	531	782	426	...	...	...	377
DF_8	654	992	785	448	764	212	...	...	...	614
DF_9	161	815	681	93	116	550	...	...	...	804
DF_{10}	377	676	806	894	893	278	...	...	...	938
DF_{11}	878	713	449	373	522	598	...	...	...	913
DF_{12}	677	302	169	142	155	590	...	...	...	718
DF_{13}	79	808	416	465	444	168	...	...	...	343
DF_{14}	544	648	194	895	720	29	...	...	...	992
DF_{15}	952	50	814	144	799	493	...	...	...	666
DF_{16}	201	467	173	809	740	854	...	...	...	115
DF_{17}	109	202	998	226	764	730	...	...	...	184
DF_{18}	4	61	287	747	416	802	...	...	...	815
DF_{19}	991	60	817	37	582	230	...	...	...	912
DF_{20}	504	476	709	282	19	845	...	...	...	131
DF_{21}	944	474	4	186	893	167	...	...	...	784

these numbers into tangible enterprise knowledge, this research designs a consumer demands identification technique which analyzes and identifies changes in consumer demands. This technique is explained below.

As shown in Fig. 10, consumer demand in each factor includes many appraisal words. According to the central limit theorem, when the sampling number of appraisal words is $n \geq 30$, the consumer demands in each factor are normally distributed. Therefore, this research assumes that the consumer demands in each factor are normally distributed, and under the 95% confidence interval the frequencies of consumer demand occurrences would fall into the range of $[\mu + 2\sigma, \mu - 2\sigma]$. Therefore, when the frequency of consumer demands found in consumer demand occurrences is out of the 95% confidence interval range, then this is defined as an obvious change in consumer demand factors.

Equation (9) calculates the mean value of the frequency of consumer demand occurrences per month, where t is the time set ($t \in \{t_j, t = 1, 2, 3, \dots, n-1\}$). Equation (10) calculates the standard deviation for the frequency of consumer demand occurrences, where x_t stands for the frequency of consumer demand occurrences for each month.

$$\mu = \frac{1}{n-1} \sum_{t=1}^{n-1} x_t \quad (9)$$

$$\sigma = \sqrt{\frac{1}{n-2} \sum_{t=1}^{n-1} (x_t - \mu)^2} \quad (10)$$

Using the example, we explain the results of the calculations from eqs. (9) and (10). As summarized in Table 7, t_n specifies the time set, μ stands for the mean value, σ stands for the standard deviation, and DC indicates whether consumer demands have changed. If the company is interested in whether consumer demand factors have changed in t_{10} , we should first use Table 7 to find out the frequencies of appearance for $DF_1 \sim DF_{21}$ during t_{10} , and if the frequencies of the appearance of consumer demand factors ($DF_1 \sim DF_{21}$) are larger than $\mu + 2\sigma$ or smaller than $\mu - 2\sigma$ during t_{10} , this indicates the consumer demands factors have changed. On the other hand, if the frequencies of the appearance of consumer demand factors ($DF_1 \sim DF_{21}$) are smaller than $\mu + 2\sigma$ or larger than $\mu - 2\sigma$ during this time, this indicates that consumer demand factors have not changed.

Case study

Based on the above-mentioned analysis tools, this study develops a computer-based approach for analyzing consumer demands. This section describes an implementation of this system using C#, and a case study is used to evaluate the effectiveness of this approach.

Fig. 11 Collection of eWOM content

eWOM Collection	Appraisal Extraction	Appraisal Word Classification	Frequency of Consumer Demands Occurrence	Consumer Demands Identification
Input Topic: 麥當勞 Choose The Information Source ☐ Xuite ☐ Yahoo部落格 (Yahoo Blog) ☐ 天空部落 (Yam Blog) ☒ 無名小站 (Wretch Blog) ☐ 痞客邦 (Pixnet Blog) Date Range ☐ All ☒ 2012/ 1/ 1 to 2012/ 6/30	Search	Collection Result		
		Information Source	Number of Collection	eWOM Content
		Xuite	200	102
		Yahoo部落格 (Yahoo Blog)	200	95
		天空部落 (Yam Blog)	200	89
		無名小站 (Wretch Blog)	200	153
		痞客邦 (Pixnet Blog)	200	127

Prototype

The research set-up includes an Intel Core2 Duo E6420–2.13G PC, running Microsoft Windows XP Professional, Internet Information Services (IIS), Microsoft SQL Server 2008, and Microsoft Visual Studio 2010.

Screenshots of the system are presented in Figs. 11–15. Fig. 11 shows the user interface screen for content collection, Fig. 12 shows the semantic analysis and extraction of the content, while Fig. 13 shows the classification of the appraisal words. Fig. 14 shows the frequency results of consumer demand

occurrence, and Fig. 15 presents the results of consumer demands identification.

System evaluation from a user satisfaction perspective

In order to examine the effectiveness of the proposed mechanism and assist strategic planning managers, marketing personnel, and R&D personnel to carry out marketing strategies, this study used a user satisfaction questionnaire to conduct a system evaluation, adopting the approach from Li and Chang (2009), Chen and Chen (2012), and Pai et al. (2013b). The

Fig. 12 Semantic analysis and extraction of eWOM content

eWOM Collection	Appraisal Extraction	Appraisal Word Classification	Frequency of Consumer Demands Occurrence	Consumer Demands Identification	Unit: Thousand			
Co-Occurrence Frequency								
	11 食物品質 (food quality)	12 食物價格 (food price)	13 食品創新 (food innovation)	14 食品的稀有性 (food rarity)	15 天然食品 (natural food)	16 食物味道 (food flavor)	17 食物口感 (food mouthfeel)	18 食物份量 (serving size)
手藝 Handicraft	0	0	0.147	0	0.421	0.269	0.753	0
可口 Delicious	0	0	0.457	0	0.214	0.423	0.876	0
巧妙 Refinement	0.87	0	0.952	0.147	0.036	0.123		
友善 Friendly	0	0	0	0	0	0		
主動的 Pro-Active	0	0	0	0	0	0	0	0
光滑的 Smooth	0	0	0	0	0.413	0.423	0.961	0
好吃 Delicious	0	0	0	0	0	0.634	0.867	0.573
好吃的 Yummy	0	0	0	0	0	0	0	0
不斐 Expensive	0	0.975	0	0	0	0	0	0
天價 Really Expensive	0	0.864	0	0.741	0.574	0.863	0	0
有益於健康 Healthy	0	0	0	0	0	0	0	0
平價的 Affordable	0	0.923	0	0	0.041	0.123	0.874	0
有益的 Beneficial	0	0	0	0	0.899	0.432	0.741	0
廉價 Inexpensive	0.77	0.961	0	0	0	0.635	0	0
低廉 Cheap	0	0.963	0	0	0	0	0	0
均勻 Uniform Size	0	0	0.413	0	0.741	0.423	0.853	0

Consumer demand factors

Chinese appraisal words

Fig. 13 Classification of appraisal words

literature review was used as the basis of this study, and the results were used to carry out the design of user satisfaction questionnaires items. The items in the instrument were rated on a five-point Likert scale, with 1 = strongly disagree, 3 = undecided, and 5 = strongly agree.

This research was conducted using both control and experimental groups. The results of a system evaluation showed that the proposed method could be used as an effective basis for product and service planning, and that it could assist strategic planning managers, marketing personnel, as well as research and development departments. In the case of the control group, the participants evaluated the traditional questionnaire surveys on consumer needs. For the experimental group, the participants were provided

access to the proposed method and were then surveyed on their opinions as to the accuracy and effectiveness of the method, given their professional knowledge and judgment. Finally, based on the surveys of the two groups and a t-test, we analyzed the level of satisfaction with these methods to determine whether any significant differences existed between the traditional approaches (marketing surveys) for analyzing consumer demands and the proposed approach. Convenience sampling was applied in this study, and the questionnaires were administered to students of executive master of business administration (EMBA) programs from three universities in southern Taiwan. The students were asked to evaluate the system used in this study. However, only one of the universities was willing to fully participate

Fig. 14 Frequency results of consumer demands occurrence

eWOM Collection | Appraisal Extraction | Appraisal Word Classification | Frequency of Consumer Demands Occurrence | Consumer Demands Identification

Calculate Frequency of Appraisal Word in Consumer Demands

Time of Occurrence Year: 2012 Month: 6 Enter

	1/06	2011/07	2011/08	2011/09	2011/10	2011/11	2011/12	2012/01	2012/02	2012/03	2012/04	2012/05	2012/06	
01. 可靠性(Reliability)	379	718	311	1702	1282	1008	0	1608	1302	224	483	1106	1336	
02. 回應性(responsiveness)	1388	909	1140	1181	966	902	337	1875	251	1677	1453	598	1875	
03. 勝任性(competence)	322	1313	1225	1897	1311	20	1342	375	1366	1263	496	1413	1243	
04. 親近(access)	498	1169	1806	1201	777	80	1267	575	608	812	1313	459	1256	
05. 禮貌(courtesy)	698	1787	390	1757	280	1925	714	174	213	1461	1794	55	1690	
06. 溝通(communication)	1495	236	250	557	1065	88	498	1241	1319	849	1902	19	1638	
07. 信賴(credibility)	1618	1145	1811	293	768	1864	374	835	912	1876	1222	24	1879	
08. 安全(security)	1134	1870	1342	67	1210	1515	1597	995	742	1321	460	1260	1909	
09. 瞭解/同理心(understanding/knowing)	583	1824	1041	945	1839	404	509	1006	1096	1143	55	832	867	
10. 有形(tangible)	1176	1182	480	386	1527	104	1046	859	291	763	1082	963	807	
11. 食品品質(food quality)	762	1119	522	1815	1391	468	1199	233	776	532	1699	1330	1430	
12. 食物價格(food price)	741	1917	136	1036	908	35	1777	49	1222	1748	1146	599	1271	
13. 食品創新(food innovation)	372	547	647	984	1016	511	1754	1874	1210	1659	271	283	642	
14. 食品的稀有性(food rarity)	1405	1203	836	1638	1632	865	550	1555	1139	125	1008	1183	1350	
15. 天然食品(natural food)	1491	1825	1245	148	875	302	1339	811	553	112	1295	1874	62	
16. 食物味道(food flavor)	707	1173	1943	1703	1094	83	261	148	727	305	685	1102	158	
17. 食物口感(food mouthfeel)	10	913	67	536	1765	215	951	138	267	1059	1420	181	428	
18. 食物份量(serving size)	216	962	177	883	491	808	1260	58	516	245	1809	1188	1677	
19. 位置(convenience of location)	853	1616	563	890	20	1684	1379	960	1078	17	1773	199	1372	
20. 合計(Total)	1000	1020	764	957	1495	675	1076	1166	860	1477	1677	1574	1306	

Next

Fig. 15 Results of consumer demands identification

Calculate of Analyzing Consumer Demands					Results of Estimation and Confidence Intervals			Result of Consumer Demands Identification	
	2012/03	2012/04	2012/05	2012/06	μ	$\mu+2\sigma$	$\mu-2\sigma$		
01. 可靠性(Reliability)	1873	1705	1808	1059	1446.0731...	1988.9964...	903.14984...	02. 回應性(responsiveness)	
02. 回應性(responsiveness)	1303	1680	1608	805	1480.7317...	2020.6856...	940.77777...	08. 安全(security)	
03. 勝任性(competence)	1127	1343	1356	1039	1421.1951...	1957.31437...	885.07587...	09. 瞭解/同理心(understanding/ knowing)	
04. 親近(access)	1931	1057	1805	1360	1561.5121...	2156.6694...	966.35497...	11. 食物品質(food quality)	
05. 禮貌(courtesy)	1606	1098	1833	1395	1455.2037...	2352.0718...	872.76477...	12. 食物價格(food price)	
06. 溝通(communication)	1393	1557	1191	1510	1494.3414...	2082.3183...	906.36459...	15. 天然食品(natural food)	
07. 信賴(reliability)	1551	1012	1818	1479	1522.6585...	2079.50902...	965.80805...	16. 食物味道(food flavor)	
08. 安全(security)	1874	1624	1700	2661	1512.5853...	2037.0718...	988.09890...	17. 食物口感(food mouthfeel)	
09. 瞭解/同理心(understanding/ knowing)	1205	1971	1847	2722	1481.4146...	2034.1147...	928.71448...	18. 食物份量(serving size)	
10. 有形(tangibles)	1053	1557	1422	1419	1438.95122...	1980.7925...	897.10992...	19. 位置(convenience of location)	
11. 食物品質(food quality)	1454	1058	1952	1711	1527.1707...	2082.9390...	971.40241...	20. 餐廳環境(restaurant environment)	
12. 食物價格(food price)	1251	1168	1048	2541	1431.5609...	1958.9926...	904.12926...	21. 餐廳風格(restaurant style)	
13. 食品創新(food innovation)	1287	1376	1519	1689	1431.2682...	1976.3124...	886.22409...		
14. 食品的稀有性(food rarity)	1548	1710	1063	1730	1480.5853...	2031.9860...	929.18467...		
15. 天然食品(natural food)	1665	1148	1328	2173	1496.4146...	2031.5167...	961.31255...		
16. 食物味道(food flavor)	1610	1394	1480	782	1479.1707...	2070.0311...	888.31027...		
17. 食物口感(food mouthfeel)	1395	1074	1387	934	1505.5365...	2058.5138...	952.559349...		
18. 食物份量(serving size)	1917	1516	1915	2431	1551.4390...	2163.6412...	939.23675...		
19. 位置(convenience of location)	1427	1983	1704	2142	1474.9268...	2074.9652...	874.88839...		
20. 餐廳環境(restaurant environment)	1989	1930	1371	2119	1502.4634...	2113.3062...	891.62055...		
21. 餐廳風格(restaurant style)	1980	1808	1356	1313	1519.1219...	2137.0202...	901.22367...		

in this work, and only eighteen participants were willing to take part in the evaluation of the system. These participants who took part in the experiment all had a bachelor's degree in business administration, and were mainly from small and medium-sized enterprises in Taiwan. The participants

included strategic planning managers and marketing personnel, as well as research and development personnel. Each participant had to possess related knowledge and real-world experience of using marketing surveys and consumer demand analysis. When the participants took part in

Table 7 Consumer demands identification

		Time set t ($t = 1 \sim n$)													
		t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}				
Consumer demand factors j ($j = 1 \sim 21$)	DF_1	92	66	86	51	54	91	59	93	22	49	68	114	70	Y
	DF_2	43	15	30	17	41	73	47	26	53	54	38	73	37	
	DF_3	34	38	76	45	3	16	94	21	8	91	37	95	28	
	DF_4	29	83	90	29	73	92	19	25	76	82	57	116	59	
	DF_5	75	83	100	69	36	43	20	45	96	19	63	116	57	Y
	DF_6	32	32	61	8	95	74	3	5	45	99	39	101	29	
	DF_7	99	84	8	67	34	92	89	84	77	16	70	127	65	Y
	DF_8	63	41	63	66	34	33	16	56	37	96	45	78	33	Y
	DF_9	72	35	74	85	23	74	49	84	9	23	56	109	54	Y
	DF_{10}	47	27	2	35	15	15	35	2	63	38	27	65	28	
	DF_{11}	34	10	40	38	22	56	68	15	7	98	32	72	14	Y
	DF_{12}	89	68	18	75	97	18	73	8	21	20	52	118	55	Y
	DF_{13}	99	98	24	10	4	15	64	83	12	19	45	121	54	Y
	DF_{14}	78	97	92	78	71	43	33	61	40	68	66	109	67	
	DF_{15}	31	75	10	27	31	99	82	22	43	87	47	105	43	
	DF_{16}	17	34	33	2	87	46	69	53	71	88	46	97	44	
	DF_{17}	57	55	29	66	66	88	84	18	15	92	53	104	47	
	DF_{18}	37	25	95	31	61	9	85	33	73	22	50	106	48	Y
	DF_{19}	85	99	29	24	68	50	84	32	40	3	57	109	51	Y
	DF_{20}	7	84	62	61	39	90	97	40	15	1	55	116	53	Y
	DF_{21}	47	36	93	98	27	34	49	21	36	4	49	101	42	Y

Table 8 Results of the performance evaluation of the proposed consumer demands analysis method

Questionnaire item	Control group		Experimental group		<i>T</i>	<i>P</i>
	Mean	S.D.	Mean	S.D.		
1. The analytical range of the consumer demands analysis is very wide.	3.1	0.851	3.566	0.874	−1.945	*0.028
2. The consumer demands analysis reduced the time needed for market planning.	3	0.827	3.466	0.74	−2.041	*0.022
3. The consumer demands analysis can be used to analyze information about market changes.	3.133	1.016	3.633	0.722	−2.076	*0.021
4. The consumer demands analysis does not require any training or expertise.	2.966	0.929	3.5	0.81	−2.214	*0.015
5. The data sources for the consumer demands analysis are reliable.	3	0.689	3.666	0.85	−2.942	**0.002
6. The analytical results of the consumer demands analysis are objective.	3.066	1.167	3.566	0.874	−1.916	*0.03
7. The consumer demands analysis is effective.	3.333	1.54	3.433	0.46	−0.387	0.35

*:*p* value < 0.05 indicates significance at 0.05 **:*p* value < 0.01 indicates significance at 0.01

this study, they had all been working for at least 15 years, and were all company leaders or experts in their line of business. Therefore, the results derived from their opinions could be said to have expert validity.

The results of the analysis are shown in Table 8. The responses to questionnaire items 1 to 6 indicate that the method proposed in this work could be seen as effective. The results also indicated that the mechanism can be used to retrieve reliable information about a changing market and consumers. The results of the eWOM analysis on consumer demands can be seen as both objective and reliable, and so useful for market planning. This study also interviewed the participants, and they stated that one of the benefits of the method was that it provided timely and extensive consumer information, which is less likely to be obtained with traditional questionnaire surveys. The analytical results for questionnaire item 7 were not significant. The participants agreed that this study presented a new analytical method to analyze consumer demands. While verifying the application and value of this method requires long-term study, many participants thought that eWOM analysis may be what the business world wants, and that the analytical results of this study might be able to help enterprises to innovate and improve their products or services.

In summary, the results of analyzing the questionnaire indicate that the method proposed in this study is better than traditional questionnaire surveys. It may thus be able to offer timely and extensive analytical results that help managers make better decisions. However, many participants thought that the method still requires long-term analyses and observations to verify its reliability. A short-term study was carried out in this worked because we wanted to find out any problems with this approach

and then work to address them. As such, future studies are needed to extend the work of the current project.

Conclusions and perspectives

A computer-based approach was developed in this study to analyze consumer demands, and this can help enterprises develop their product lines and improve their services. This work provides primary findings and has the following contributions to the literature. First, a user satisfaction survey was conducted to reveal the effectiveness of this system, and the results prove that it is capable of analyzing consumer demands, as well as providing marketers and managers with valuable market information. Secondly, a computer-based approach was developed in this study to improve traditional methods of analyzing consumer demands. Finally, this paper employed computer programs to analyze critical consumer demands. Computerized analysis makes it easier for enterprises to collect and analyze this kind of data, while enhancing the accuracy of the process.

Based on the computer-based approach presented in this work, this study has three suggestions for future works. First and foremost, future studies should include processes to filter out eWOM information published by enterprises in order to increase the validity of the results. Secondly, this study used a questionnaire with marketers and managers for the purpose of system evaluation and to identify potential issues for future enhancement. However, the evaluation process should be continued for at least three to five years for more objective results. Therefore, a longitudinal study is suggested to determine the feasibility of this mechanism. Finally, the system presented in this study can only determine consumer demands valued by

eWOM, and is not capable of prioritizing which consumer demands deserve more improvement efforts. As a result, future studies are suggested to take a step further in designing a computer-based approach that could prioritize the items that require the most attention.

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