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Exploring energy-saving refrigerators through online e-commerce reviews: an augmented mining model based on machine learning methods

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Abstract

Purpose – Based on climate issues and carbon emissions, this study aims to promote low-carbon consumption and compel consumers to actively shift to energy-saving appliances. In this big data era, online reviews in social and electronic commerce (e-commerce) websites contain valuable product information, which can facilitate firm business strategies and consumer comparison shopping. This study is designed to advance existing research on energy-saving refrigerators by incorporating machine learning models in the analysis of online reviews to provide valuable suggestions to e-commerce platform managers and manufacturers to effectively understand the psychological cognition of consumers.

Design/methodology/approach – This study proposes an online e-commerce review mining and management strategy model based on "data acquisition and cleaning, data mining and analysis and strategy formation" through multiple machine learning methods, namely, Bayes networks, support vector machine (SVM), latent Dirichlet allocation (LDA) and importance–performance analysis (IPA), to help managers.

Findings – Based on a case study of one of the largest e-commerce platforms in China, this study linguistically analyzes 29,216 online reviews of energy-saving refrigerators. Results indicate that the energy-saving refrigerator features that consumers are generally satisfied with are, in sequential order, logistics, function, price, outlook, after-sales service, brand, quality and space. This study also identifies ten topics with 100 keywords by analyzing 18 different refrigerator models. Finally, based on the IPA, this study allocates different priorities to the features and provides suggestions from the perspective of consumers, the government and manufacturers.

Research limitations/implications – In terms of limitations, future research may focus on the following points. First, the topics identified in this study derive from specific points in time and reviews; thus, the topics may change with the text data. A machine learning-based online review analysis platform could be developed in the future to dynamically improve consumer satisfaction. Moreover, given that consumers' needs may change over time, e-commerce platform types and consumer characteristics, such as user profiles, can be incorporated into the model to effectively analyze trends in consumers' perceived dimensions.

Originality/value – This study fills the gap in previous research in this field, which uses small-sample data for qualitative analysis, while integrating management ideas and proposes an online e-commerce review mining and management strategy model based on machine learning methods. Moreover, this study considers how consumers' emotional and thematic preferences for products affect their purchase decision-making from the perspective of their psychological perception and linguistically analyzes online reviews of energy-saving

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refrigerators using the proposed mining model. Through the improved IPA model, this study provides optimizing strategies to help e-commerce platform managers and manufacturers.

Keywords Energy-saving refrigerator, Online review, Text mining, Sentiment analysis, Low-carbon consumption

Paper type Research paper

1. Introduction

With the rapid development of social networks and electronic commerce (e-commerce), an increasing number of consumers are choosing online shopping, and a growing number of online reviews are being posted on the Internet daily (Zhao *et al.*, 2020). According to the "2019 China Electric Online Market Analysis Report," in the first quarter of 2019, the retail sales of home appliances exceeded 2,200 bn yuan, and total online retail sales reached 1,700 bn yuan. JD.com, as the largest online retailer of home appliances and consumer electronics in China, maintains its top status, with a 61% share. Nevertheless, China's online shopping market maintains a rapid and steady growth trend. From macro-policies to corporate promotions, the government and enterprises are working together to promote trading up. The online market is a strong engine for the growth of the home appliance industry. As a combination of traditional retail and information consumption, online shopping conforms to the trend of new trading up (Wu and Song, 2020).

However, against the background of the dramatic expansion of the consumer market for household appliances, a series of problems emerged. For example, a report released by the International Energy Agency in March 26, 2019 showed that global energy consumption reached a record high of 33.1 billion tons of CO_2 emissions in 2018, which increased by 1.7% from 2017 and was the highest growth rate since 2013. The power sector accounted for nearly two-thirds of this growth, which was largely concentrated in Asia. Climate projections indicate that average global surface warming increases nearly linearly with cumulative carbon emissions, and CO_2 emission reduction is key to mitigating continuing climate deterioration (Williams *et al.*, 2017). As the world's top carbon emitter, China experiences serious environmental pollution problems, such as haze caused by high-carbon emissions. Thus, developing a green low-carbon economy is imperative. As important aspects of a low-carbon economy, how to promote low-carbon consumption, how to compel consumers to actively shift to green low-carbon consumption and how to stimulate green low-carbon consumption market activities should be solved urgently.

Meanwhile, people's home appliance consumption entered the stage of quality consumption. With the upgrading and transformation of China's consumption structure, consumers shifted from focusing on quantitative satisfaction to pursuing qualitative improvement as well as from imitative batch consumption to personalized and diversified consumption (Wen *et al.*, 2019). Therefore, price is no longer a decisive factor for consumers in making purchase decisions. Energy-efficiency level, exquisite appearance, excellent performance and other consumption upgrading factors have become progressively important to consumers. The key factors influencing consumers' psychology regarding these upgrading factors and satisfaction with them are the main issues discussed in this study.

In the traditional analysis of energy-saving appliances, structured data or small samples are commonly used, which are prone to selection bias and estimation bias, thereby leading to incorrect or incomplete analysis results. Large-sample research involving unstructured data is necessary in the future. With the rise of online shopping platforms, such as JD.com, Taobao and Suning, big data-based research is also being applied to energy-saving appliances (Safarzadeh *et al.*, 2020). Online reviews in social media and e-commerce websites contain valuable product information (Sun *et al.*, 2019).

User-generated content, also known as word of mouth (WOM), has become an important part of online shopping, as consumers evaluate products based on past reviews (Ukpabi and Karjaluoto, 2018). The Internet extended WOM to online platforms, which is called electronic WOM (eWOM) and refers to “any positive or negative statement made by present or previous customers about a product, service or company, which is made available to large audiences via the Internet” (Abubakar and Ilkan, 2016). Owing to the proliferation of profit-motivated eWOM, consumers tend to rely on trusted sources of information or eWOM popularly known as electronic referrals (eReferrals), which refer to “any positive or negative statement made by a close ally about a product or company, which is made available to friends, relatives, colleagues and acquittance via the Internet,” and its effect depends on the degree of ties shared by the sender and receiver(Al-Htibat and Garanti, 2019). The differences between the two concepts are that eWOM includes reviews from individuals from different social classes and locations with limited social ties, whereas eReferrals include reviews from individuals sharing social ties and belonging, for the most part, to the same social class. Specifically, eReferral information can be transmitted among friends, family members and group members sharing common social ties (Abubakar and Ilkan, 2016).

JD.com, the domestic e-commerce giant, already has more than 400 million users in 2020. Due to the relative independence and noninterference of consumers from online shopping platforms, they have few direct or indirect social relationships, although they do refer to other consumers’ reviews when making online purchases. Such information has a significant impact on consumers’ purchase behavior and can help them make improved decisions. Furthermore, business owners can employ such information to enhance the quality of their services and products and devise new marketing strategies. Viewing comments has become a necessary part of online shopping, and research found that online reviews can influence consumers’ shopping decisions. Consequently, research on online reviews surged and emphasized the use of new analytical techniques (Cheng *et al.*, 2019). From the perspective of consumers and taking energy-saving refrigerators as a case study, utilizing online reviews to continuously analyze the development trend of energy-saving appliances, assess the service management quality of online e-commerce platforms and determine consumers’ needs is necessary to stimulate the development of a low-carbon economy in China.

Consumers’ sentiment tendencies can be observed in online comments. Online shopping websites such as JD.com and Taobao simply categorize online product reviews as either “good” or “bad.” Such a coarse-grained classification typically possesses numerous errors. Some consumers may choose “good” for certain reasons but express dissatisfaction in their review. Therefore, an enhanced method to directly analyze online reviews and reveal consumers’ actual sentiment tendencies is necessary. Various sentiment analysis methods were developed in different fields (Budhi *et al.*, 2021). Among supervised machine-based sentiment analysis methods, the support vector machine (SVM) model is the most widely used. An SVM is a classifier trained using annotated data to obtain the best separated hyperplane/line to accurately classify new sample data into different categories. This study employs an SVM to classify consumers’ sentiments in online reviews. In addition, owing to the diversity of consumers’ needs for products, tapping into the multidimensional features in online reviews is important. However, comment texts for products are extensive and typically accompanied by various evaluation noises. Thus, managers experience difficulties filtering feature words from comment texts to gather useful information. The probabilistic topic model garnered extensive attention from scholars because of its significant advantages in topic recognition and semantic mining. Among the numerous topic models, the latent Dirichlet allocation (LDA) model first proposed by Blei *et al.* (2012) is the most representative. This model meets scholars’ expectations and provides satisfactory results in the complex subject recognition and topic structure extraction of text data.

To address the above issues, this study uses online reviews from JD.com as its research subject to achieve the following objectives: (1) to analyze the importance of various features of energy-saving refrigerators from the perspective of consumers, (2) to examine consumers' satisfaction trend and perception dimension and (3) to present managerial implications and suggestions to help e-commerce platform managers and practitioners improve their management and marketing strategies. On the one hand, this study can provide decision support for the development of the energy-saving home appliance industry from the perspective of multiple stakeholders and help managers make improved production or marketing decisions. On the other hand, this study can provide a reference to similar studies in the field of low-carbon consumption in China to stimulate the development of a low-carbon economy.

2. Literature review

This study uses the bibliometric tool – Citespace to select information from the Web of Science core database and search for keywords with the topic "energy-saving appliance" while filtering the document type to only articles. At the end of January 2021, 927 data samples were obtained. Keywords are important signs responding to research hotspots. In this study, keyword nodes are selected to show the high-frequency words among the keywords and manually adjusted to obtain the keyword co-occurrence map, which is presented in Figure 1. Large nodes reflect a high number of keyword occurrences. As shown in the figure, research on energy-saving appliances is conducted in two main areas. One area is the consumption direction of energy-saving appliances, represented by the word "consumption" (Wang *et al.*, 2019). The other area is consumer behavior, represented by the term "behavior" (Waris and Hameed, 2020). Further analysis is performed based on the keyword nodes and relevant literature.

2.1 Energy-saving appliance consumption

As a vital element in production and consumption, energy has become a major concern as demand increases sharply, along with rapid industrialization and urbanization, in China. In 2016, household energy consumption reached 54,209 tons of standard coal equivalent, approximately 12.4% of China's total energy consumption, in which household appliances accounted for the largest proportion (Zhang *et al.*, 2018). Rapid economic growth and the improvement of living standards lead to the continuous growth of appliance and energy consumption and use (Nejat *et al.*, 2015). However, against the background of the dramatic expansion of the consumer market for household appliances, a series of environmental problems emerged. These problems promote the development of a low-carbon economy

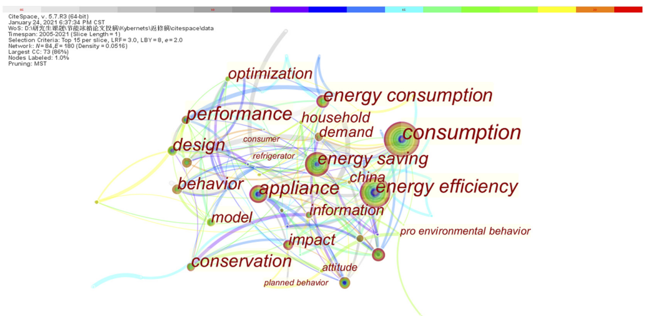

Figure 1. Keywords co-occurrence map

based on low-carbon consumption and drive the rapid development of the energy-saving home appliance consumption market. In addition, the promotion of energy-saving appliances in residential households is one of the most important ways to achieve national sustainable development goals (Wiederhold and Martinez, 2018).

Energy-saving appliance consumption behavior refers to green appliance purchase by consumers to conserve resources and protect the environment (Sharma and Foropon, 2019). Numerous studies on factors influencing consumer purchase behavior exist, most of which focused on the influence of psychological and situational factors, with theory of planned behavior as the most cited theory (Lim and An, 2021). Olson argued that consumers will make trade-offs between a product's energy-saving attributes and traditional functional features, and consumers' willingness to purchase will be considerably reduced when the value of the attributes does not compensate for the traditional functional value (Olson, 2013). Based on theory of norm activation, other studies used behavioral attitudes and social norms as antecedent variables of behavioral willingness and emotions as mediating variables of responsibility attribution and personal norms. The results of such studies showed that extended models have higher explanatory power for behaviors than original models (Han, 2014). Based on signal theory and attitude–behavior theory, data from a survey of 440 South African home appliance users were analyzed using structural equation modeling to explore the drivers of consumer attention to energy-efficiency labels (Issock *et al.*, 2018). The aforementioned studies suggested that consumers' energy-saving appliance purchase behavior is influenced by a combination of psychological and external situational factors.

The results of the analysis of the Citespace bibliometric tool show that most existing studies on energy-saving appliances are based on the qualitative analysis of micro-research data, such as questionnaires or semistructured interviews. Few studies quantitatively analyzed and assessed the current development of energy-saving appliances from a microscopic and multidimensional perspective in practical management applications. However, small samples may lead to attribute omissions or biased analysis results, thereby failing to comprehensively and systematically portray the characteristics and patterns of consumer behavior and energy-saving appliance attributes and resulting in the large variability in the obtained conclusions. In this big data era, online reviews can provide a stable database for this study. Therefore, this study aims to utilize large-scale online reviews to continuously analyze the development trend of energy-saving appliances, evaluate the quality of the service management of multiple stakeholders and discuss the needs of consumers to stimulate the development of a low-carbon economy in China.

2.2 Methods and analysis of online reviews

Online reviews are unstructured texts published by consumers on independent review sites or third-party e-commerce platforms. Such reviews are utilized to express consumers' experience with a particular service or brand and are often accompanied by a ranking or rating (Ahani *et al.*, 2019). The China Internet Network Information Center survey showed that among 413 million Chinese online shoppers, 77.5% refer to reviews when shopping online. When consumers purchase home appliances online, they typically browse online reviews submitted by other consumers, which serve as important references for their own purchase decisions (Budhi *et al.*, 2021).

A number of e-commerce websites, such as JD.com and Taobao, established online review systems to encourage consumers to post product reviews, which consequently changed consumer behavior patterns and gradually affected consumer purchase decisions. For example, consumers pay increasing attention to online reviews when deciding on what movies to watch, what stocks to invest in and so on (Ryu *et al.*, 2010). In addition, many online communities, such as Facebook and Douban, provide platforms for consumer discussions. Therefore, online reviews provide a promising means for discovering consumer opinions and sentiments on purchased and utilized products. Numerous studies examined online reviews from different perspectives, such as their effect on consumer expectations (Narangajavana *et al.*, 2017) and role as consumer satisfaction determinants (Guo *et al.*, 2017a) and psychological influences (Stamolampros and Korfiatis, 2018). Consumers' post-purchase online reviews on e-commerce platforms are proven useful sources, revealing consumer insights (Vriens *et al.*, 2019) and consumer needs (Timoshenko and Hauser, 2017). Thus, mining and analyzing consumer online reviews are useful to multiple stakeholders.

The first step in analyzing online reviews is collecting online reviews from e-commerce platforms on the Internet (Gour *et al.*, 2021). One widely used approach is via a web crawler, which is a program or software that traverses the web and downloads web documents automatically and methodically (Abukausar *et al.*, 2013). The second step involves mining the useful information hidden in online reviews. Typical technologies for this procedure include topic extraction and sentiment analysis.

Topic extraction is employed to analyze hidden topics in texts and mine underlying themes and semantic text structures and is widely cited in many fields. In terms of topic models, the most popular methods are probabilistic graphical models, in which topics are typically viewed as distributions over words, and documents are treated to share underlying topics of different proportions from the perspective of probability (Blei *et al.*, 2004). LDA is a typical example (Chen *et al.*, 2019), which models documents with a fully Bayesian paradigm and thus is preferred for adjustable priors to closely refer to the nature of specific documents, topics and terms (Blei *et al.*, 2003). Based on these qualities and advantages, LDA modeling is applied to different types of text data and sentiment analysis. LDA was widely used in prior studies to discover key dimensions from online reviews (Guo *et al.*, 2017b), identify influential subjects from text messages (Pournarakis *et al.*, 2017), derive a set of variables to predict the success of crowdfunding projects (Yuan *et al.*, 2016), capture key aspects of products from reviews (Lee *et al.*, 2016), cluster landmarks to recommend and optimize tourists' travel plans (Sun and Lee, 2017) and so on. Research findings adequately proved that LDA is a scientific and effective method for processing text data.

Meanwhile, sentiment analysis can help decision makers access emotional information expressed by consumers by analyzing the content of a text (Budhi *et al.*, 2021). The SVM is a key machine learning method commonly used in sentiment analysis (Markopoulos *et al.*, 2015). The SVM has a solid theoretical foundation and performs classification more accurately than most other algorithms in many applications. Various studies claimed that the SVM may be the most accurate method for text classification (Moraes and Valiati, 2013). In existing research on binary sentiment classification, different machine learning algorithms were used to develop methods for binary sentiment classification (Medhat *et al.*, 2014), in which the SVM was regarded as one of the most effective machine learning algorithms (Balazs and Velásquez, 2016).

The above research suggested that to promote the consumption of energy-saving home appliances and stimulate the development of China's low-carbon economy, conducting not only qualitative analysis but also multidimensional exploratory analysis from a micro-perspective is necessary. However, existing studies may lead to biased or wrong conclusions owing to small-sized samples. In this big data era, online review samples can provide considerable data support. Therefore, this study explores the sustainability strategies of energy-saving home appliances from the perspective of consumers by using multiple existing methods and taking energy-saving refrigerators as an example. Furthermore, this study addresses not only computer-related but also management issues. To enhance the relevance of the research results to management decisions, this study employs the classical importance–performance analysis (IPA) management model, which is an ideal service evaluation model (Wang *et al.*, 2020), and proposes a novel model based on a decision paradigm.

3. Methodology

3.1 Research setting and design

This study selects JD.com, which is the largest online sales platform for household appliances in China, as the source of the online review data. According to the 618 big data of JD.com in 2018, the sales volume of the home appliance sector exceeded RMB two billion in eight minutes, and the sales of refrigerators such as Midea were considerably ahead. Therefore, this study selects the online review data of six well-known brands on the JD.com platform as the dataset.

Most studies on energy-saving appliances are based on the qualitative analysis of micro-research data, which may lead to attribute omissions or biased analysis results. In this big data era, online reviews can provide a stable database in this filed. This study intends to develop an online review mining model for energy-saving refrigerators based on machine learning methods. Based on the SVM and LDA models, first, this study proposes an integrated sentiment analysis model to measure consumers' sentiments by calculating their satisfaction. Second, this study explores the comment topics to understand the sensory perception dimension. The colloquial nature and short length of e-commerce review texts may lead to problems of loud noise and sparse semantic information. Therefore, this study incorporates Bayesian networks (BNs) and proposes an improved IPA model combined with the SVM and LDA models to analyze features and keywords from two dimensions, namely, performance and importance. In addition, this study provides suggestions on energy-saving refrigerator implementation to e-commerce platform and manufacturing managers to help them enhance their perception of consumers' psychological cognition and to stimulate low-carbon consumption in China. Furthermore, the research paradigm can be used as a reference for similar research.

A flowchart of the methods used in this study is presented in Figure 2. A description of the methods is provided in this section as well as that of the case. The final analysis results are presented in the subsequent section.

3.2 Data collection and preprocessing

Online reviews contain parametric information of products sold online. Consumers' consumption experience and other valuable information can serve as references for other

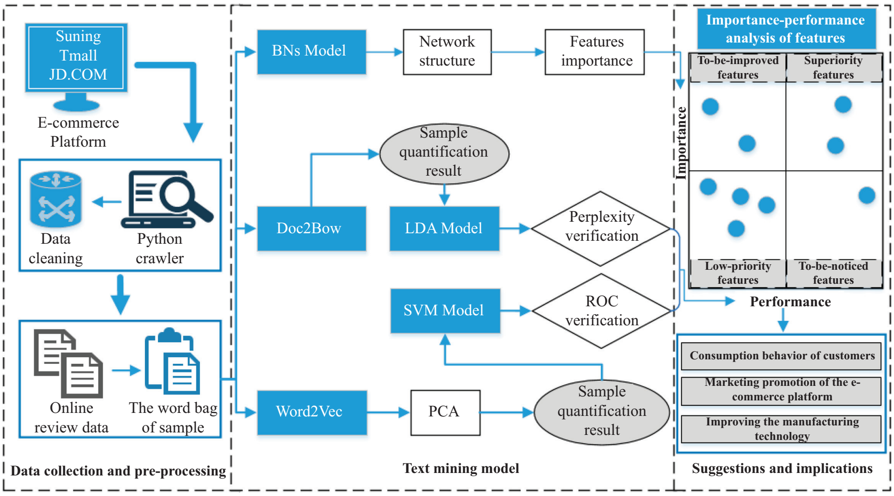

Figure 2.
Flowchart of the methods

consumers choosing similar products. This study selects online reviews of energy-saving refrigerators as the original dataset. The textual data required for this study include parametric attributes and consumer reviews, which include user ID, comment time, content, user rating and so on.

A web crawler, which is a program or software that traverses the web and downloads documents automatically and methodically, is widely used to collect information from the Internet. This study uses Python to write a web crawler (the code is provided in Appendix) to collect online review data individually, specifically, content, scores and time of the textual data. Empty and duplicate comments are deleted, and null data are removed. This study compares the field length of each comment and comments with the same field length to intercept the first 50% of the text for textual matching. If the contents are similar, then they are deduplicated.

A total of six brands are collected, namely, Haier, TCL, Midea, Gree, Konka and Siemens. One or two full-energy-level refrigerators are selected for each brand. Nearly 30,000 comments are collected. Table 1 presents the refrigerator brands, energy-saving rating, type and number of online reviews.

3.3 Topic sentiment analysis integrated model

3.3.1 SVM model. The SVM model is a classifier that uses annotated data for training to obtain the best separated hyperplane/line to accurately classify new sample data into different categories. This algorithm works well on dichotomous classification problems. Compared with neural network methods, the SVM method requires less data to train a model. Hence, the SVM model is highly suitable for emotion classification. The basic idea of this model is presented below.

First, defining the sample training set $D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\}$, $y_i \in \{-1, +1\}$ and to separate the different categories in D, a hyperplane in the sample space represented by D is divided.

In the sample space, the division of the hyperplane is described by a linear equation.

$$W^T x + b = 0. \tag{1}$$

Brand	Energy-saving rating	Type	Number of reviews
Haier	Level 1	BCD-310WDPG	1,967
	Level 2	BCD-201STPA	1,689
	Level 3	BCD-160TMPQ	1,397
TCL	Level 1	TCLBCD-211TWF1	1,879
	Level 2	TCLBCD-260TWZ50	1,057
	Level 3	TCLBCD-118KA9	2,079
Midea	Level 1	BCD-655WKPZM	999
	Level 2	BCD-226WTM	1,967
	Level 3	BCD-190CM	1,403
Gree	Level 1	BCD-230WETCL	1,897
	Level 2	BCD-580WIPDCL	1,935
	Level 3	BCD-436WPQCL	1,788
Konka	Level 1	BCD-330BX4S	1,655
	Level 2	BCD-458EBX4S	1,867
	Level 3	BCD-192MT	917
Siemens	Level 1	KG28US12EC	1,787
	Level 2	KM48EA20TI	1,954
	Level 3	KG23N111EW	979
Total			29,216

Table 1. Details of six refrigerator brands

$$W = (w_1, w_2, \ldots w_d), \tag{2}$$

where W is a normal vector, which is used to determine the direction of the hyperplane, and b is the displacement term, which is used to indicate the distance between the hyperplane and origin.

The hyperplane can be determined by W and b and denoted as $(W,\ b)$. The distance from any point x in the sample space to the hyperplane is expressed as

$$r = \frac{|W^T x + b|}{||W||}. \tag{3}$$

If the hyperplane (W, b) can correctly classify the training samples, then $(x_i,\ y_i) \in D$. If $y_i = +1$, then $W^T x_i + b > 0$. If $y_i = -1$, then $W^T x_i + b < 0$. That is, the following conditions must be met.

$$\begin{Bmatrix} W^T x_i + b \geq +1, y_i = +1 \\ W^T x_i + b \leq -1, y_i = -1 \end{Bmatrix}. \tag{4}$$

"Support vector" represents a training sample point that conforms to the above formula and is closest to the hyperplane. The margin between the samples is expressed as

$$\gamma = \frac{2}{||w||}. \tag{5}$$

The final model is trained to find the maximum margin, where γ max is $\frac{1}{||W||}$ maximum, which is equivalent to making $||W||^2$ the smallest, to acquire the basic SVM type.

$$\min_{w,b} \frac{1}{2}||w||^2,$$

$$s.t. \, y(W^T x_i + b) \geq +1 \ , \ i = 1, 2, \ldots, m. \tag{6}$$

This study uses Python to develop the sentiment classification model. As SVM is a supervised machine learning model, preparing the samples classified for model training is necessary. This study uses Python to write a web crawler then selectively crawls refrigerator reviews on the JD.com platform. More than 2,000 five-star positive reviews and more than 2,000 one-star negative reviews are collected as the original samples. The emotional tendencies in the samples are manually distinguished, in which 1 is positive, and 0 is negative. The specific process is described below.

3.3.1.1 Text preprocessing. This study uses Python and the Jieba Chinese word segmentation library to conduct the sample text-based data processing. In the word segmentation process, all punctuations and various symbols by regularity are removed, the pure text is obtained and the stop word library and self-built vocabulary are loaded for the word segmentation. The stop word bank used by the latest version of the Natural Language Processing and Information Retrieval (NLPIR) participle of the Chinese Academy of Sciences is selected for this study.

3.3.1.2 Word2Vec model training. SVM model training supports only numerical samples. Thus, the text data sample must be quantized, that is, converted into numerical data. In 2013, Google's Word2Vec open source project triggered a wave of research and the application of word vectors (Turian *et al.*, 2010). The Word2Vec word vector is widely used in natural language processing tasks, such as text sentiment analysis, as a basic technology for deep learning in the field of natural language processing. In this study, first, the Word2Vec word vector model construction method provided in the well-known NLP processing library

Gensim is used to construct the model. Second, the text is converted into a vector. The collected comments (over 4,000) are segmented, then the trained Word2Vec model is used to convert each word into a vector. Third, the vector of an entire comment is weighted and outputted, and all sample comments are processed in turn. Finally, a two-dimensional matrix is obtained. The number of rows represents the number of comments, and the number of columns represents the 400 dimensions set by the model.

3.3.1.3 Feature extraction. The representation of texts by vectors typically encounters sparse vector space and high feature dimension problems. In view of this situation, feature dimension reduction processing is necessary. Dimensionality reduction can reduce the feature dimensions of a script, decrease the number of iterations during model training and eliminate similar semantic features. This reduction can improve the accuracy and recall rate of sentiment classification and efficiency. The principal component analysis (PCA) method, also known as K-L transformation, which is a linear data analytic method based on statistical properties, is chosen for this study (Zhou *et al.*, 2013). PCA mainly relies on the position information of a sample in space. Moreover, PCA assumes that a sample set holds the largest variance along certain directions (the largest variance ensures the smallest data loss after projection) and projects the sample onto a straight line where the directions are located. As a result, the correlation and noise among the samples are eliminated during the projection process. The PCA method is used to consider the correlation among feature items and transform an original feature document matrix into a low-dimensional orthogonal feature matrix. This matrix comprises the principal components of the original feature document matrix, retaining most of the feature information from the original feature matrix. Moreover, this matrix ensures that the new features are irrelevant.

The PCA algorithm function provided in the Scikit-learn library is used to perform training estimation on the 400 sample dimensions, and Matplotlib is employed to represent the changes in the relationship between the dimensions and variance. The results are presented in Figure 3, which shows a significant turning point near approximately 80 dimensions; thus, 100 is selected in this study as the effective number of dimensions in each review to express the vector information.

3.3.1.4 SVM model training. After the positive review sample and negative review sample are processed according to the above steps, two matrices of 100 * 2,365 and 100 * 2,532 are outputted, and one dimension is defined as the emotional tendency, in which positive is defined as 1, and negative is defined as 0. Finally, the matrix is synthesized to obtain a matrix sample of 4,897 * 101. To train the SVM model, Scikit-learn's svm.SVC () function is employed, the sample parameters are inputted and the value of the adjustment penalty coefficient C is set. The larger the penalty coefficient, the higher the accuracy of the sample classification to a

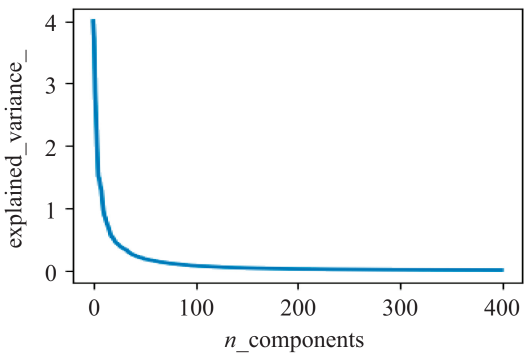

Figure 3.
PCA output result

certain extent, but the lower the generalization ability of the model. The kernel parameter in the adjustment method is set to a radial kernel function, and the probability parameter is inputted to determine whether to enable probability estimation. After a series of attempts, a reasonable parameter is determined. When C is 2, the probability is true, and the rest paraments are default, the model can obtain satisfactory results. The accuracy of this model can reach 95% after the testing samples are run.

3.3.1.5 Model test. As the SVM model constructed in this study is a supervised learning model as well as a binary classification model, evaluating it using the receiver operating characteristic (ROC) curve is the most appropriate option. In addition, to verify the accuracy of the model intuitively and scientifically, the ROC method of the Scikit-learn library and Matplotlib visualization library is employed to visualize the results of the ROC curve, which are presented in Figure 4.

The ROC curve above shows that the area under curve (AUC) output value of the training model is as high as 0.98. Combining the characteristics of the AUC and theoretical knowledge with the rationality of the model, a conclusion can be drawn that the model demonstrates high accuracy and is in line with this study's expectations.

3.3.2 LDA model. The LDA model is a text topic representation method that introduces a complete probabilistic model. Its core purpose is to compute posterior topics using Bayesian estimation based on the Dirichlet prior assumption of text topic distribution and word distribution (Jelodar *et al.*, 2019). The specific structure and its generative process are displayed in Figure 5 and described in the subsequent section.

First, a document d_i is selected according to probability $P(d_i)$. Second, the topic distribution θ_m of document d_i is sampled from the Dirichlet distribution α. Third, the topic $z_{m,n}$ of the j word of document d_i is extracted from the topic distribution θ_m. Fourth, the

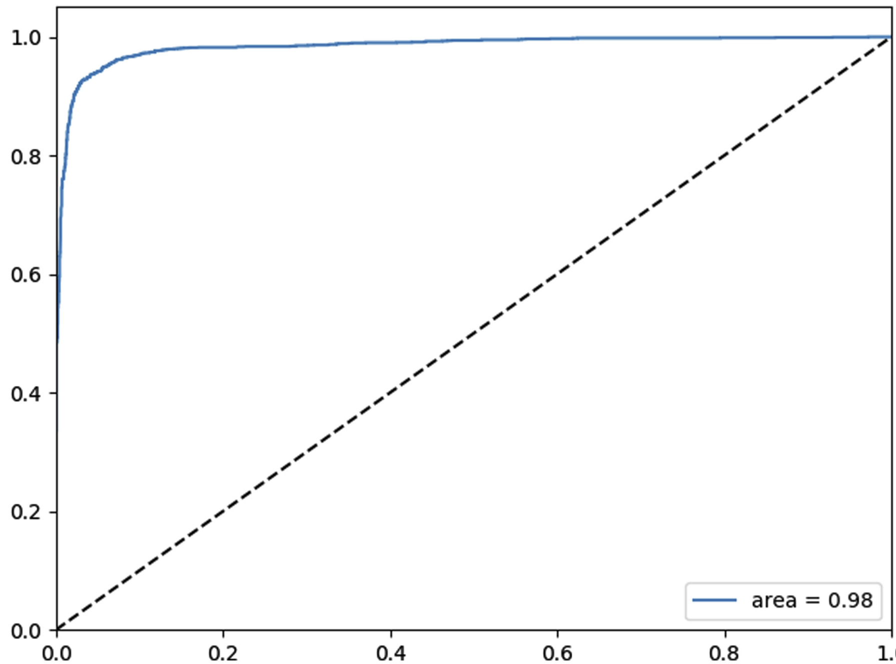

Figure 4.
ROC curve

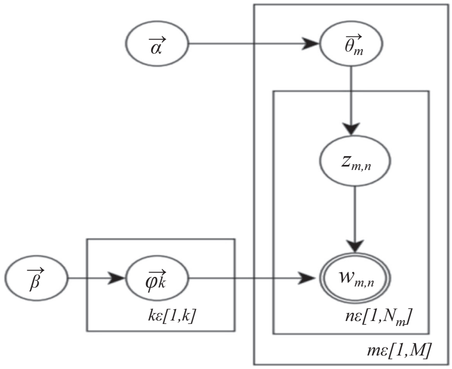

Figure 5.
LDA model schematic diagram

generated word distribution β from the LDA φ_k is sampled. Fifth, the word $w_{m,n}$ is generated by the sampling from the word distribution φ_k. The design formula is as follows:

(1) The following formula is used to generate the probability of the subject number of all the words.

$$P(\vec{z}|\vec{\alpha}) = \prod_{m}^{M} \frac{\Delta(\vec{n}_m + \vec{\alpha})}{\Delta \vec{\beta}}. \tag{7}$$

(2) As the topic number choice does not change the word distribution of the topic, the formula can be further expressed as

$$P(\vec{w}|\vec{z}, \vec{\beta}) = P(\vec{w}|\vec{\beta}) = \prod_{k}^{V} \frac{\Delta(\vec{v}_k + \vec{\beta})}{\Delta \vec{\beta}}. \tag{8}$$

(3) The corpus of the LDA model-generated probability can be expressed as

$$P(\vec{w}, \vec{z} \vee \vec{\alpha}, \vec{\beta}) = \prod_{k}^{V} \frac{\Delta(\vec{v}_k + \vec{\beta})}{\Delta \vec{\beta}} \bullet \prod_{m}^{M} \frac{\Delta(\vec{n}_m + \vec{\alpha})}{\Delta \vec{\alpha}}. \tag{9}$$

The number of topics is the most important parameter in the LDA topic model, and estimating the number of topics as accurately as possible can substantially improve the efficiency of the optimization model. In this study, first, the relationship between the number of topics and perplexity is investigated to set the number of topics from 1 to 100 and extract the perplexity of the model during training and the perplexity of the test sample set. By doing so, it can be concluded that an increase in the number of topics will lead to an increase in the perplexity. Therefore, for the refrigerator purchase reviews, as the number of text topics is not large, and considering the effect of the model application, the number of topics is set to 10 in this study.

Similarly, based on Python, the corresponding model training parameters and number of topics are set to 10, the processed sample is inputted, and the LDA model method is employed to train the model. After numerous trials and comprehensive model perplexity values, the number of training iterations is set to 50. Meanwhile, 2,000 words for a single training session is the most effective number, and the remaining parameters are set to default values.

3.3.3 Integrated sentiment analysis model. To explicitly analyze the factors that consumers pay attention to when making online purchases and their sentiment toward energy-saving refrigerators, an integrated sentiment analysis model based on the LDA and SVM models is proposed. Moreover, the sentiment analysis model is proposed to calculate consumers' satisfaction with each energy-saving refrigerator topic. The sentiment analysis model is defined as follows:

(1) The relevance between the nine features and ten topics extracted previously is calculated using the LDA model, and the result is transformed into a 9 * 10 matrix R (Relevance).

$$R = \{A_{ij}\},\ \ i = 1, 2 \ldots 9, j = 1, 2 \ldots 10, \tag{10}$$

where A_{ij} represents the relativity between the $i - th$ feature and $j - th$ topic.

(2) The comment samples are evaluated individually, and the topics are extracted from the LDA topic model to obtain a 1 * 10 matrix D (Deduction).

$$D = \{B_i\},\ \ i = 0, 1, 2...9, \tag{11}$$

where B_i represents the inferred value between the comment and i-th topic.

(3) The SVM model is used to analyze the sentiment of each comment, in which a positive sentiment is marked as 1, and a negative sentiment is marked as −1. The entire sample is analyzed, thereby obtaining matrix P.

$$P = \{C_n\},\ \ Cn\ \in \{-1, 1\}. \tag{12}$$

(4) The following formula is employed to calculate the score of all the features in each comment.

$$S = R * D * P, \tag{13}$$

where S (Score) represents the score matrix of a single review of the nine features, R represents the relevance matrix of the nine features and ten topics, D represents the relationship matrix of a single review and the ten topics and P represents the sentiment preference score of a single comment. A matrix result set containing N 1 * 9 is obtained, and the nine values in each row represent the scores of the nine features from the online reviews.

(5) All the matrices are summarized, and the sentiment scores of the entire sample for the nine features are obtained, which is a 1 * 9 matrix G (Goal).

$$G = \sum_{k=1}^{n} Sk. \tag{14}$$

3.4 Improved IPA model

With the above SVM and LDA models, the sensory dimension and importance rankings of energy-saving refrigerator attributes are identified from the perspective of consumers. This study aims to help managers and manufacturers improve their management and marketing strategies to enhance the green home appliance industry to stimulate low-carbon consumption in China and understand consumers' perception of various topics and elements. Therefore, this study introduces an improved IPA model based on a BN model and combines managerial ideas with the above results to suggest effective strategies.

3.4.1 BN model. BNs were first introduced as graphical models that can encode the joint probability distribution of a set of discrete random variables (Pearl, 1991). BNs consist of a directed acyclic graph and a set of conditional probability distributions in each network variable and are information representation frameworks that combine causal knowledge with probabilistic knowledge to make deterministic reasoning logically clear and easy to understand (Sierra *et al.*, 2009). Moreover, BNs can obtain more effective results using a Bayes model compared with simple regression analysis or random forests given a sufficient number of training samples (Ruz *et al.*, 2020). A hierarchical BN is used to build a model to analyze human emotions and can find complex emotions in a document by establishing a relationship among the topic modelings and analyzing emotions (Fuji *et al.*, 2013). Traditional relationship analysis seeks only to determine the degree of importance between each factor but fails to quantify specific relationships. To effectively analyze the relationship between the features, a BN model that also considers probability is proposed in this study. According to this relation, variable x is independent from the other variables if it has parents, as follows:

$$P(x_1, x_2, \dots, x_n) = \prod_{i=1}^{n} p(x_i | parents(x_i)). \tag{15}$$

3.4.2 IPA model. The IPA model was first proposed by Martilla (Martilla and James, 1977) and soon applied to the catering industry. The IPA model is an exceptional method for evaluating services in various fields (Sever, 2015). The theoretical basis of the IPA method is the expected difference model. The basic idea of this method is to determine the importance of each factor improvement by comparing the importance and actual performance of each factor. Thus, managers can use limited resources on the "blade" to optimize resources effectively. In this study, the themes extracted by the LDA model and their thematic elements are used as the objects. The saliency and expressiveness methods are as follows:

Importance: With the BN model completed previously, the subject reviews are divided separately into different thematic features, and the importance ranking of each feature is obtained. Moreover, the distribution of the topics in all the samples is counted, and the importance ratio is used as a significant performance indicator.

Performance: The frequency of the occurrence of positive and negative comments in each topic is calculated with strict probability statistics based on the LDA and SVM models. Based on the analysis results of the integrated sentiment model, emotional satisfaction with each topic expressed by the energy-saving refrigerator consumers in the comments is obtained, which can be used to demonstrate product performance from the perspective of consumers.

4. Results

4.1 Characteristic feature evaluation

High-frequency words are defined as vocabulary that is highly frequent and can reflect, to a certain extent, consumer information focused on a product in comments. High-frequency words from online reviews provide the basis for the extraction of product features. All major e-commerce platforms attach considerable importance to the guiding effect of online reviews by consumers; thus, official high-frequency words are displayed on platforms. The official high-frequency words on the JD.com platform selected for this study are also displayed, and the official data are relatively accurate. Therefore, this study initially adopts the officially provided high-frequency vocabulary.

By processing the high-frequency words and extracting nouns as the main elements, the features from the online reviews in the overall consumption process can be generally obtained. However, synonyms exist in the Chinese language; thus, summarizing words with similar meanings is necessary. The statistical results of the high-frequency words are summarized and optimized iteratively. For example, "mute," "noise," and "sound" are classified as sound, and "color," "appearance," and "golden" are classified as outlook. By doing this procedure multiple times, the high-frequency words are classified into different labels.

Through multiple iterative optimizations, improved keyword frequency statistical results and features from the online reviews are obtained. A total of ten features are summarized in this study, namely, platform, logistics, brand, after-sales service, outlook, space, function, sound, quality and price. The ten features are the most cited concerns in consumer post-purchase feedback based on the consumer online reviews. In addition, these features can express the main composition of the consumers' satisfaction to a certain extent. Thus, the ten features are used to analyze their interrelationships and construct the consumer sentiment analysis model. The partial results of the high-frequency keywords summarized into the features are shown in Table 2.

In the summarization process, several words appear multiple times, whereas other words appear less or more. Therefore, an obvious difference in consumers' concern for each product is observed. A high frequency indicates that the consumer pays increased attention to the corresponding feature factor, and the feature is prominent in the product.

As ten features from the online reviews are summarized in this study, the quantification relationships between them should be analyzed further. Therefore, the specific interrelationships and importance ranking of the ten features in the level-one energy-saving refrigerators are obtained using the BN model, and the results are shown in Figure 6.

In Figure 6, the blue circle represents the target variable as the input parameter, the red circle represents the predictor variable as the output parameter, and the color depth of the red circle represents the importance of the features in the model. In the BN structure diagram, the satisfaction score as the target variable is connected to the other ten variables through the arrow. Satisfaction is related to the other features, but a gap exists between the importance of each feature. The network diagram also shows a correlation between the features, and the connection is reasonable based on life experiences, such as the impact of a platform on logistics and after-sales service and the relationship between after-sales service and price and brand and so on.

The importance ranking of the features is as follows: function, space, price, after-sales service, sound, logistics, brand, platform, quality and outlook, and their importance ratio is 0.1227, 0.1177, 0.1041, 0.1032, 0.0995, 0.0934, 0.0926, 0.0894, 0.0888 and 0.0887, respectively. From the importance ranking, a conclusion can be drawn that consumers pay attention to

Number	Features	High-frequency keywords
1	Platform	Platforms, JD.COM, Tmall, Gome and Suning
2	Logistics	Logistics, fast, soon, high-speed, delivery, arrival, package, not yet, receive, speed, deliveryman, sent, courier, delivery staff, Bro and Freight
3	Brand	Brand, Midea, Haier, Hisense, TCL, Siemens, domestic, Gree, Jing Hong, domestic goods, Samsung and famous brand
4	After-sales	After-sales, patient, complaint, premium, Agio, refund, workers, service, consumer service, attitude, installation, service attitude and pack
5	Outlook	Exterior, pretty beautiful, beautiful, exquisite, color, white, red and silver
6	Space	Storage, centimeter, capacity, tall, drawer and design
7	Function	Function, performance, usage, egg plaid, practical, machine, human, configuration, high-tech, panel, cold wind and no-frost
8	Space	Sound, murmur, noise, mute, ring, very light and noisy
9	Quality	Quality, craftsmanship, odor, compressor, temperature, quality control, inferior quality, heat, second hand, door panel, seam, leaking cold wind, smog, roughness, vibration, scratches, refrigeration, freezing, freezer, packaging, workmanship, quality, effect, frost-free, frosting, freezing, cost-effective, cooling effect and durable
10	Price	price, worth, full reduction, giveaways, price reduction, price increase, activity, affordable, cost-effective, cheap, too expensive and not expensive

Table 2.
Summary of features

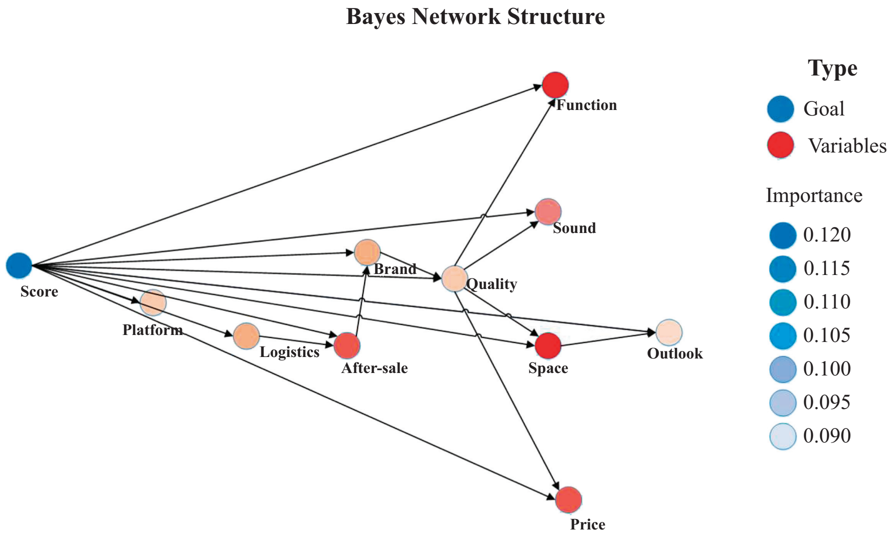

Figure 6.
Bayes network structure

different features when shopping online. The feature that consumers pay the most attention to is function, whereas the feature that consumers pay the least attention to is outlook, which indicates that consumers are generally concerned about a product's quality rather than its appearance.

Similarly, the importance ranking of the features in level two is as follows: brand (0.1255), logistics (0.1205), quality (0.1123), price (0.1112), function (0.1073), outlook (0.1065), platform (0.0931), space (0.0835), after-sales service (0.0731) and sound (0.0672). The importance ranking of the features in level three is as follows: space (0.1243), quality (0.1229), function (0.1133), brand (0.0991), logistics (0.0982), outlook (0.096), platform (0.0938), after-sales service (0.0927), price (0.0843) and sound (0.0754).

4.2 Topic extraction with sentiment analysis

To analyze consumers' sentiments toward the different features in the online reviews, this study integrates the SVM and LDA methods to develop the sentiment analysis model. A total of ten energy-saving refrigerator topics from the online review data are obtained using the LDA model, and each topic is described using ten keywords, followed by each word's relevance. The ten topics and their keywords are listed in Table 3.

Meanwhile, the confusion in the model is 188.3, which is relatively low compared with that in other models; thus, the LDA model is better. Moreover, in the comparison of the 100 obtained keywords with the feature words in the previous step, 87 words are exactly the same, thereby proving the verification of the model.

To analyze consumers' sentiments toward each feature, this study first classifies the sentiment polarity of each comment into positive and negative using the SVM model. Second, consumers' satisfaction with energy-saving refrigerators is obtained using the sentiment analysis model proposed in Section 3.4. Platform is ignored in this model because the conditions affecting it are too few. The results are visualized and displayed in Figure 7.

Figure 7 shows that consumers are mostly satisfied with logistics, with the highest score of 1,083.532, followed by function, with a score of 821.168; price, with a score of 766.554; outlook, with a score of 432.4374; after-sales service, with a score of 411.4125; brand, with a

Table 3.
Topics of online reviews

Topics	Keywords and their relevance
Topic 1	Refrigerator (0.065), air-cooled (0.014), sound (0.013), material (0.012), satisfaction (0.011), send (0.011), delivery (0.010), price (0.009), feeling (0.008) and very soon (0.008)
Topic 2	Fridge (0.036), satisfaction (0.032), delivery (0.024), speed (0.022), quick (0.020), logistics (0.017), shopping (0.014), order (0.014), express (0.013) and package (0.012)
Topic 3	Fridge (0.066), master (0.019). Panasonic (0.017), jd.com (0.015), compare (0.014), exactly (0.012), air-cooled (0.011), appearance (0.011), delivery (0.010) and specially (0.010)
Topic 4	Fridge (0.049), sound (0.015), satisfaction (0.014), space (0.012), consumer service (0.011), air cooling (0.010), logistics (0.010), place (0.010), order (0.009) and already (0.008)
Topic 5	Fridge (0.055), delivery (0.025), master (0.020), use (0.019), power (0.017), feeling (0.013), received (0.013), convenient (0.013), jd.com (0.011) and worthy (0.010)
Topic 6	Fridge (0.043), master (0.019), satisfaction (0.014), installation (0.012), appearance (0.011), shopping (0.011), beautiful (0.011), worthy (0.011), buy (0.011) and sound (0.010)
Topic 7	Refrigerator (0.047), jd.com (0.020), appearance (0.016), air-cooled (0.016), no frost (0.013), bro (0.012), express (0.012), price (0.011), logistics (0.011), delivery (0.011)
Topic 8	Point (0.020), refrigerator (0.015), Haier (0.011), worthy (0.008), jd.com (0.007), consumer service (0.007), daily (0.006), many (0.006), panel (0.005) and freezer (0.005)
Topic 9	Fridge (0.038), feels (0.021), temperature control (0.019), computer (0.016), promotion (0.015), style (0.015), convenient (0.015), freezer (0.014), drawer (0.011) and refrigeration (0.011)
Topic 10	Refrigerator (0.027), baby (0.026), explanation (0.021), feeling (0.014), smell (0.014), received (0.014), satisfaction (0.013), get through (0.011), shopping (0.011) and exactly the same (0.010)

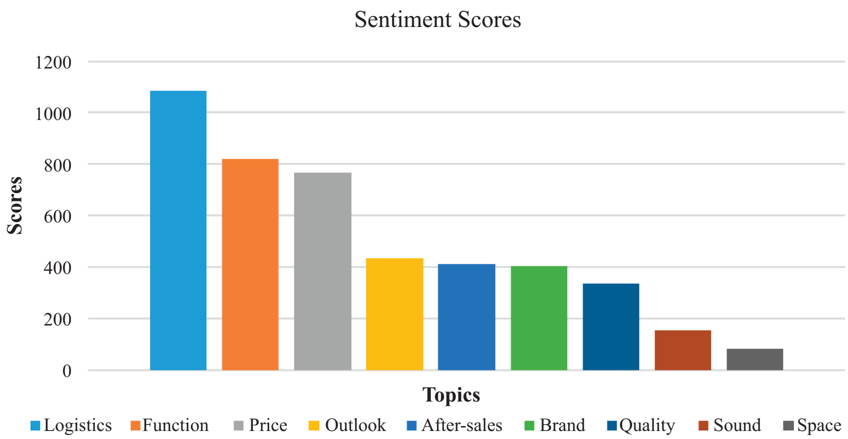

Figure 7.
Sentiment score ranking

score of 402.0579; quality, with a score of 334.7215; and space, with a score of 83.6114, which is also consumers' least concerned feature.

4.3 IPA

In this study, the improved IPA method is used in combination with the BN and integrated sentiment models to obtain the saliency and expressiveness of each feature. The average of the performance and importance means is divided into IPA quadrants. Figures 8–10 present the results of the different energy-saving refrigerator levels.

The IPA analysis model distributes the nine features into four quadrants through data processing. The above three figures show that refrigerators with different energy-efficiency levels demonstrate different performances from the perspective of consumers.

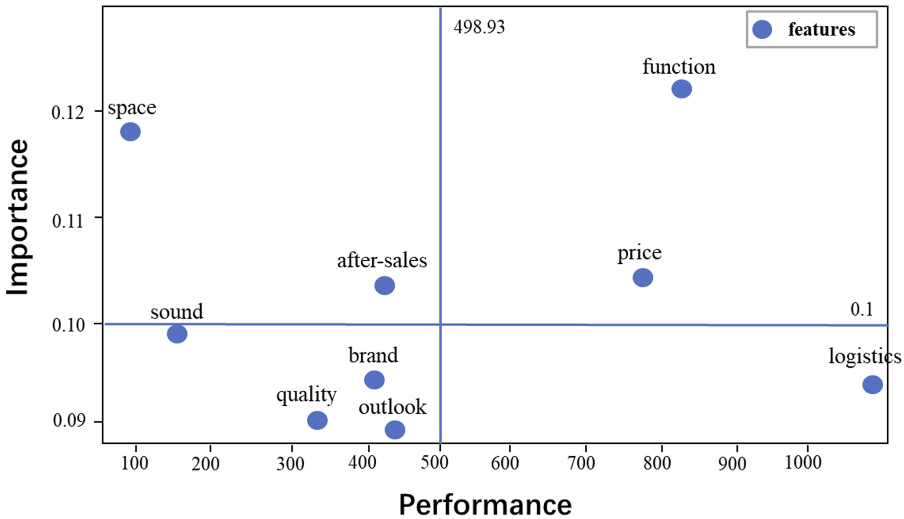

Figure 8. Importance–performance analysis of level 1

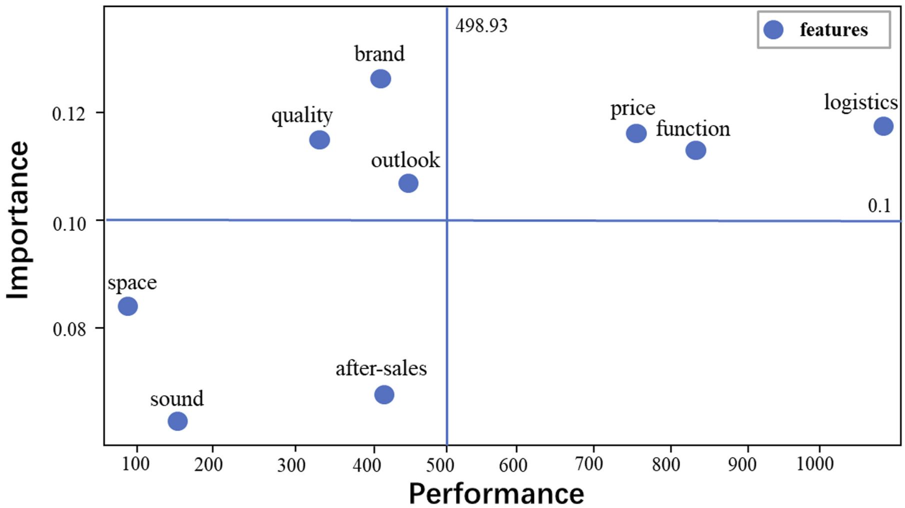

Figure 9. Importance–performance analysis of level 2

(1) *Superior features of energy-saving refrigerators are presented in the first quadrant.* For consumers, the performance and importance of the features in this quadrant are high, which means that this quadrant plays an important role in improving consumer satisfaction. The performance of the features basically meets consumer expectations. Furthermore, satisfaction is high. The features in the first quadrant are the advantageous selling points of energy-saving refrigerators and thus should be maintained. For the level-one energy-saving refrigerators, price and function are distributed in the first quadrant. For the level-two energy-saving refrigerators, besides price and function, logistics is distributed in the first quadrant. For the level-three energy-saving refrigerators, only function is in the first quadrant. Generally, as

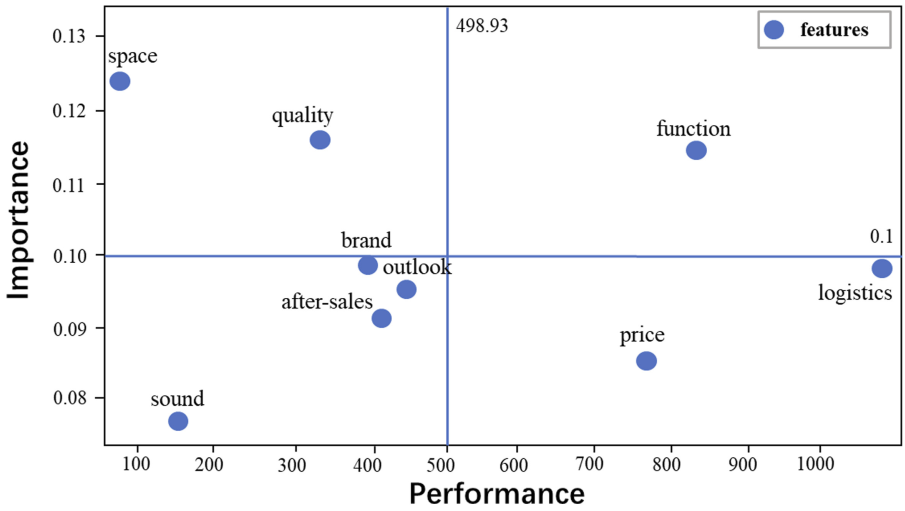

Figure 10.
Importance–performance analysis of level 3

e-commerce platforms lack physical store-related costs, the price of an energy-saving refrigerator sold online will be lower than that of the same type of energy-saving refrigerator sold in a physical store. Therefore, the price and function of a refrigerator are highly recognized by consumers. At the same time, the JD.com platform has logistics distribution centers throughout the country; thus, consumers are also satisfied with the logistics speed. Thus, e-commerce platform managers and energy-saving refrigerator manufacturers should continue to maintain the quality of function and price features. Meanwhile, e-commerce platforms should improve their logistics distribution centers and maintain logistics efficiency.

(2) *Features that require improvement are presented in the second quadrant.* From the perspective of consumers, for the features in this quadrant, performance is low, but importance is relatively high. For the level-one energy-saving refrigerators, space and after-sales service are distributed in the second quadrant. For the level-two energy-saving refrigerators, brand, quality and outlook are in the second quadrant. For the level-three energy-saving refrigerators, space and quality are in the second quadrant. The features in this quadrant require improvement. With the improvement of living standards, consumers' refrigerator and corresponding after-sales service requirements increased. Therefore, energy-saving refrigerator manufacturers should continuously improve their technology to meet consumers' requirements. At the same time, e-commerce sales platforms should maintain their after-sales services.

(3) *The low-priority energy-saving refrigerator features are presented in the third quadrant,* in which performance and importance are low. Except for the feature common in all the energy-saving refrigerator levels, namely, sound, different energy-saving refrigerators have different features in this quadrant. The features in this quadrant have a low priority and need not be developed immediately. However, they should not be completely ignored. In the case of limited resources, prioritizing development is not advisable. In the future, as the market matures, the features in this quadrant can be upgraded further. The features of outlook, space and brand are involved in the entire manufacturing process. Therefore, improving manufacturing technology will likewise improve these features.

(4) *Features that managers should pay attention to are shown in the fourth quadrant,* in which performance is high, but importance is low from the perspective of consumers. Only logistics and price in the level-one and level-three energy-saving refrigerators are distributed in the fourth quadrant. Although consumers are satisfied with the features in this quadrant, they pay little attention to them. Moreover, though these energy-saving refrigerator features are recognized by consumers, their perception level is relatively low. The above features can be explored further to transform them into competitive product advantages. However, stakeholders need not invest too much time and energy in maintaining and improving these refrigerator features in a timely manner.

4.4 Suggestions and implications

Research on energy-saving home appliances has the following objectives: to optimize online sales platform management measures from the perspective of consumers, to stimulate the low-carbon consumer market and to reduce the high-energy consumption of home appliances to combat climate change. This study provides the following recommendations to achieve the three aforementioned objectives effectively.

(1) Improve service quality to reduce consumer complaints. The IPA results show that consumers express dissatisfaction with after-sales services. Consumers have a high degree of perception for this feature, which should be improved. With the improvement of living standards, consumers' requirements increased; thus, e-commerce platforms should strengthen staff management. Measures such as improving service quality, increasing the professional service knowledge of service personnel and enhancing the level of service are necessary.

(2) Maintain brand image and improve the manufacturing process. The above analysis shows that consumers perceive a high degree of importance for the following energy-efficient refrigerator features: function, space, sound and quality. This finding indicates that in addition to external features, such as service or logistics, consumers are concerned about the quality of energy-saving appliances. Thus, manufacturers should provide quality and reliable products to maintain brand image in the minds of consumers.

(3) Pay attention to the supply chain of online sales platforms and offer attractive prices. The managerial and pricing strategies of e-commerce platforms should consistently be optimized. The IPA results show that features such as price and logistics are in the first quadrant, thereby indicating that JD.com is doing well in terms of these features. As e-commerce platforms lack physical store-related costs, the prices of products sold online will be lower than those of similar products sold in physical stores. Meanwhile, JD.com has logistics distribution centers throughout the country; thus, consumers are satisfied with the logistics speed. Other e-commerce platforms should optimize their entire supply chain to increase consumers' satisfaction and behave more favorably toward products online compared with products in brick-and-mortar stores when setting prices.

(4) Strengthen focused marketing promotion and provide more accurate marketing strategies. Owing to the different energy-efficiency levels of energy-saving appliances, consumers may be concerned about different points. Combined with user research or after-sales consultations, e-commerce platforms can develop various marketing strategies based on products' energy-efficiency levels by texting messages, issuing coupons and so on to stimulate low-carbon consumption

behavior and increase user repurchase or retention rates. Moreover, community e-commerce is currently a hot topic in China; thus, integrating major community e-commerce platforms and conducting joint marketing activities by season or holiday should be considered to stimulate green appliance sales.

(5) Reduce negative and meaningless comments. The above analysis shows that with the improvement of the online shopping market, consumers developed a habit of reading reviews before making purchases. The above analysis indicates that reading reviews can influence consumers' decision-making. Therefore, high-quality reviews are important to consumers. E-commerce platforms can reduce meaningless reviews by increasing secondary reviews, encouraging reviews with pictures and increasing the length of review texts.

5. Conclusions

Since the Copenhagen Climate Conference in 2009, energy saving and carbon emissions have received unprecedented attention, and a global boom in green product sales has been observed. Meanwhile, as e-commerce continues to grow, online platforms offer a vast market for green appliances, such as energy-saving refrigerators. In view of the development trend of low-carbon consumption and the influence of consumption upgrading and other factors on consumer decisions, this study begins with the connotation and requirements of online e-commerce and the development of the green home appliance industry, taking energy-saving refrigerators as an example. In addition, this study presents multidimensional evaluation results from the perspective of consumers using online reviews. Moreover, this study proposes an online e-commerce review mining and management strategy model based on "data acquisition and cleaning, data mining and analysis and strategy formation" to help managers effectively understand energy-saving refrigerators, identify strengths and weaknesses in the manufacturing and marketing management processes and provide a reference to other studies, such as similar product/service recommendations or consumer preferences, to stimulate the development of a low-carbon economy in China.

Based on a systematic review of existing research on the energy-saving home appliance industry and low-carbon economy, this study determines that small-sample research data and difficulties in analyzing customer preferences increase research challenges owing to the upgraded consumption structure. However, in this big data era, big data and related methods can provide satisfactory solutions to this problem. This study aims to provide a machine learning method for mining online reviews of energy-saving refrigerators using the BN, SVM, LDA and IPA models; the PCA algorithm and other relevant methods. The model evaluation proves that the proposed model achieves satisfactory results. First, the BN model is used to analyze the importance and interrelationships of the characteristic features of refrigerators with different efficiency levels from online reviews. Second, the SVM and LDA machine learning algorithms are employed to identify consumers' sentiment tendencies based on the features from the review texts and the contributing features of energy-saving refrigerators from the massive number of reviews. Third, an IPA model is developed to help managers understand the importance and performance of each feature. Finally, recommendations from three perspectives, namely, consumers, e-commerce platforms and manufacturers, are presented to provide new ideas for sales platform promotion planning and manufacturing. The results show that the energy-saving refrigerator features that consumers are generally satisfied with are, in sequential order, logistics, function, price, outlook, after-sales service, brand, quality and space. A total of ten topics with 100 keywords are also identified through the analysis of 29,216 reviews of 18 different refrigerator models. The IPA model is constructed by combining the importance and performance of each feature of the different-level energy-saving refrigerators, and it was found that consumers' perceptions and satisfaction levels differ for refrigerators with different energy-saving levels. Based on this information, different improvement recommendations are offered.

In terms of limitations, future research may focus on the following points. First, the topics identified in this study are derived from specific points in time and reviews; thus, the topics may change with the text data. A machine learning-based online review analysis platform could be developed in the future to dynamically improve consumer satisfaction. Moreover, given that consumers' needs may change over time, e-commerce platform types and consumer characteristics, such as user profiles, can be incorporated into the model to effectively analyze trends in consumers' perceived dimensions.

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Further reading

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Appendix

Web crawler code:

```
def geturls(urls1,score):
    urls2=[]
    for url in urls1:
        url1 = url[:-18] + score + url[-17:]
        url2 = "&pageSize=10&isShadowSku=0&rid=0&fold=1"
#2&pageSize=10&isShadowSku=0&rid=0&fold=1
        urls2.append(url1)
        urls2.append(url2)
        #print(url1)
    return urls2

def getResult(xurl):
    results =[]
    statue =0
    Referer = {"Referer": "https://item.jd.com/" + xurl.split("&")[-8].split("=")
        [-1] + ".html"}   # https://item.jd.com/3459483.html
    headers.update(Referer)
    sleep(1)
    response = requests.get(xurl, headers=headers)
    response.encoding = "gbk"
    html = response.text
    if(html==""):
        statue= 1
        results.append(statue)
        results.append("")
        return results
    print(html)
```

```
        fetch =xurl[65:].split("&productId=")[0]+"("
        result1 = html.strip(fetch)
        result = result1.strip(");")
        return result
def writeComments(filename,result):
        com_dic = json.loads(result)
        comments = com_dic["comments"]
        c = len(comments)
        lines=[]
        for i in range(c):
                doubledic = comments[i]
                score = doubledic.get("score")
                comment = doubledic.get("content")
                time = doubledic.get("creationTime")
                line ="score:" + str(score) + "comment:" + str(comment) +
                 "time:" + str(time) + "\n"
                lines.append(line)
                        with open(filename, "a")as f:
                                for lin in lines:
                                        f.write(lin)
                                        f.flush()
                                        os.fsync(f)
                                f.close()
                def function(urls,score,filename):
                        urlNoPage =geturls(urls,score)
                        buffer =[]
                        for u in range(int(len(urlNoPage)/2)):
                                for i in range(100):
```

```
finalurl =urlNoPage[(2*u-2)]+str(i)+urlNoPage[(2*u-1)]
print(finalurl)
res=getResult(finalurl)
if(isinstance(res,list)):
    print("request null>>")
    break
buffer.append(res)
for res in buffer:
    writeComments(filename,res)
```

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