

Influencing Factors and Mechanism of Book Consumer Satisfaction Based on Online Reviews (Postprint)

Authors: Lichun Yin, Wang Yue

Date: 2023-07-26T00:00:00+00:00

Abstract

[Purpose/Significance] This paper proposes a method for mining key factors affecting reader satisfaction from large-scale online product review data, and conducts an in-depth investigation into the impact patterns and magnitudes of various factors on consumer satisfaction, thereby providing a theoretical foundation for book publishing enterprises and e-commerce platforms to continuously improve reader satisfaction. [Method/Process] On the one hand, a Naive Bayes classifier is utilized to categorize reader sentiments. On the other hand, high-frequency nouns in review texts are clustered to identify the main factors influencing reader satisfaction. Based on this, the impact patterns and magnitudes of each factor are analyzed according to the principle of maximum uncertainty reduction. [Results/Conclusion] An empirical study was conducted using JD.com reviews of artificial intelligence books as an example, revealing that six factors including content and price can substantially reflect reader satisfaction (83.2%). Therefore, for book products, the main factors affecting reader satisfaction can be identified through learning from large-scale historical review data, and a simplified reader review framework can be designed accordingly to enhance readers' motivation to participate in reviewing and improve review quality. "Book content" is the most critical factor affecting reader satisfaction. When readers express different sentiments toward book content, the impact patterns and magnitudes of other factors on reader satisfaction are completely different. When readers are satisfied with book content, 89.2% of overall reviews are positive, with other factors having minimal impact, and price being the primary cause of neutral and negative reviews; when readers consider book content average, reviews tend to be neutral, with readers paying more attention to service and logistics; when readers find book content unsatisfactory, the factors affecting reader satisfaction are, in order, packaging, service quality, and price. Based on the different impact patterns and magnitudes of various factors

on reader satisfaction, book publishing enterprises and e-commerce platforms can make more targeted improvements to enhance reader satisfaction.

Full Text

Preamble

Volume 63, Issue 22, November 2019

ChinaXiv Cooperative Journal

Factors Influencing Book Consumer Satisfaction and Their Mechanisms Based on Online Reviews

Yin Lichun^{1,2}, Wang Yue¹

¹ School of Economics and Management, Heilongjiang Bayi Agricultural University, Daqing 163319

² School of Politics and Public Administration, Shandong Youth University of Political Science, Jinan 250000

Abstract

[Purpose/Significance] This paper proposes a method to mine key factors influencing reader satisfaction from large-scale online commodity review data, and deeply explores the influence patterns and degrees of various factors on consumer satisfaction, thereby providing a theoretical basis for book publishing enterprises and e-commerce platforms to continuously improve reader satisfaction. **[Method/Process]** On the one hand, a Naive Bayesian classifier is used to classify reader emotions. On the other hand, high-frequency nouns in evaluation texts are clustered to identify the main factors affecting reader satisfaction. Based on this foundation, the influence patterns and degrees of each factor are analyzed according to the principle of minimizing uncertainty. **[Result/Conclusion]** An empirical study was conducted using JD.com's artificial intelligence book reviews as an example. Six factors including content and price were found to greatly reflect reader satisfaction (83.2%). For book commodities, simplified reader review frameworks can be designed by learning from large amounts of historical review data to identify main factors affecting reader satisfaction, thereby enhancing reader participation in reviews and improving review quality. "Book content" is the most important factor affecting reader satisfaction. When readers express different emotions about book content, the influence patterns and degrees of other factors on reader satisfaction are completely different. When readers are satisfied with book content, 89.2% of overall comments are positive, with other factors having minimal influence; price is the main factor causing neutral and negative reviews. When readers consider book content average, comments tend to be neutral, with readers paying more attention to service and logistics. When readers consider book content

unsatisfactory, the factors affecting reader satisfaction are, in order, packaging, service quality, and price. Based on these different influence patterns and degrees, book publishing enterprises and e-commerce platforms can make more targeted improvements to enhance reader satisfaction.

Keywords: reader satisfaction; book online reviews; machine learning; sentiment analysis

1. Introduction

As national literacy improves, reading has become an essential part of daily life. A 2018 joint survey by Amazon (China) and the “National Reading” official website showed that respondents reading more than 10 books annually increased from 48% in 2016 to 56%. In 2017, China’s total book retail market reached 80.3 billion yuan, with B2C online retail book publications accounting for 30.13 billion yuan, representing a growth rate of 34.4% [Figure 1: see original paper]. The B2C online book publication transaction scale is projected to reach 64.61 billion yuan by 2020 [1].

Social platforms serve as primary channels for readers to share reading experiences, with “reading together” based on social networks becoming a unique behavior in the digital reading era. The rapid speed and wide coverage of information dissemination in the internet age enable readers’ shared experiences to influence large numbers of potential readers. Relevant enterprises and e-commerce platforms encourage consumer reviews and sharing through points or small vouchers, generating massive amounts of User-Generated Content (UGC). E-commerce platforms can use this for precise customer profiling to achieve targeted marketing, and through customer review management, attract potential consumers.

This study uses JD.com (China’s largest B2C online book sales platform, which surpassed Dangdang and Tmall with 36.2% market share in Q3 2017 [2]) as the platform, selecting online reviews of bestsellers in the artificial intelligence field as research objects. It identifies factors influencing reader satisfaction (evaluation dimensions) and uses machine learning methods to classify overall review sentiment (positive, neutral, and negative). Based on this, it examines the influence patterns and degrees of different factors on reader satisfaction, providing empirical evidence for book online sales platforms and publishing enterprises in review management and support for designing more effective evaluation systems.

2. Theoretical Foundation

2.1 Online Review Research

Before internet technology prevailed, people often learned about products through inquiry, considered the predecessor of online reviews [3,4]. With rapid technological development, product transactions have gradually shifted from offline to online, and channels for obtaining product information have shifted accordingly, giving rise to online reviews. Scholars widely accept C. Park and T.M. Lee's [5] definition: consumers publish positive and negative reviews of purchased products through e-commerce platforms.

After years of research accumulation, the usefulness of online reviews has been widely recognized. M.L. Jensen et al. proposed that online reviews can become a reliable information source for product quality that cannot be easily characterized before use [6]. S. Ludwig et al. demonstrated through experiments that online consumers trust review text content more than merchant product information [7]. Online reviews play a crucial role in shaping consumer cognition and perceptions of products [8-9].

Research on online reviews' impact on product sales has been extensive across multiple domains. N.N. Hodac et al. confirmed that Amazon's online product reviews influence final sales to some extent [10]. Wang Junyi and Yan Qiang found that long-text reviews directly affect sales of various mobile phone brands on JD.com [11]. J.H. Lee et al. confirmed the correlation between online reviews and movie box office [12]. W. Duan and Peng Lihui respectively verified the positive correlation between online review text volume and product sales [13,14]. Consumer purchase decision behavior also significantly impacts corporate profitability [15], and online reviews can improve consumer awareness of shopping websites and products, attract potential consumers, and enhance loyalty [16].

Online reviews not only reflect consumer experiences but also influence potential consumers' purchase intentions. Research shows that online reviews of certain products significantly affect other consumers' purchase attitudes or behaviors [17], enabling consumers to evaluate and compare multiple alternatives before purchase [18]. From the consumer perspective, online reviews provide needed information and alleviate concerns about products or services [19].

Research on consumer review motivation has also progressed. J. Heyman and D. Ariely found that when shopping websites provide economic rewards for reviews, reviewers based on market exchange principles tend to publish more favorable ratings for the website or merchant [20]. J.C. Sweeney et al. found that economic rewards damage intrinsic motivation, reducing individual effort and thus affecting review usefulness [21].

As consumers often suspect positive reviews result from economic rewards establishing a market exchange relationship with shopping websites [20], they believe negative reviews provide more valuable clues and greater influence [22]. Ning Lianju studied the impact of online negative reviews on online consumers' pur-

chase intentions from four dimensions: degree, quantity, content relevance, and professionalism [23]. Song Yuanzheng decomposed online negative reviews into undifferentiated product attribute negative reviews, merchant service level negative reviews, and logistics negative reviews, exploring their impact on purchase intentions with product type as a moderating variable [24].

Compared to applications in other media fields, online reviews have not been widely applied in the book publishing industry. J. Chevalier early studied Amazon and Barnes' online book sales data, finding that ratings and quantity both positively affected outcomes, though review length's significance varied across platforms [25]. Sun Kelin used Dangdang's book review data to prove that positive reviews positively affected book sales while negative reviews had no significant effect [26]. Ji Jingwei used regression analysis to analyze factors influencing online book sales on Douban and Dangdang [27].

2.2 Consumer Satisfaction Research

In the mid-20th century, with the prevalence of marketing concepts, the idea of "consumer satisfaction" attracted attention, though no systematic research existed at the time. In the 1960s, American scholar R.N. Cardozo formally proposed the concept of "consumer satisfaction" while exploring the relationship between consumers' pre-purchase input costs and expectations and post-purchase satisfaction [28], demonstrating experimentally that when consumers expend considerable effort to obtain a product, satisfaction may be higher than when using appropriate effort, and when products fail to meet expectations, satisfaction is lower than when they do. Since then, exploration of consumer satisfaction has surged, with numerous scholars elaborating definitions from different perspectives.

No unified conceptual definition of consumer satisfaction currently exists in academia. R.L. Oliver's 1981 and 1996 theories—"consumer satisfaction is the overall emotional response to perceived differences between prior expectations and actual experience" (expectancy disconfirmation theory) and "consumer satisfaction is the degree to which established psychological needs are fully met and products and ancillary services bring consumers pleasant emotions"—are widely recognized and represent typical definitions in the historical development of "consumer satisfaction" [29,30]. Before the mid-1980s, scholars focused on the fit between consumers' actual feelings and expectations. Later research recognized that expectations are not the sole criterion for satisfaction; other factors like the product itself and related services also affect satisfaction. In the 1990s, research focused on psychological and emotional manifestations after satisfying consumer needs. Both early and later stages share the common understanding of consumer satisfaction as a psychological state and emotional expression. For example, H.K. Hunt defined consumer satisfaction as emotion [31], H. Moezzi summarized it as the psychological state resulting from consumers' evaluation of products or services [32], and Zhang Shengliang et al. defined it as the pleasant psychology consumers perceive during consumption [33].

Internet development has fundamentally changed the nature of relationships between enterprises and consumers, making online shopping consumer satisfaction research important. For instance, Zha Jinxiang and Wang Lisheng confirmed through structural modeling that online product price advantages and quality most significantly affect consumer satisfaction [34]; L. Zhang et al. used confirmatory factor analysis and structural equation modeling to verify that computer proficiency, perceived convenience, and perceived security are determinants affecting online shopping satisfaction [35]; Li Yuping and Hu Pei proposed eight factors affecting online shopping consumer satisfaction, including product quality, merchant service, and express service quality [36]; U. Tandon et al. analyzed factors affecting consumer satisfaction in online shopping environments using data from 410 online consumers in North Indian states, revealing that website functionality, design, and transaction security all influence satisfaction [37].

Compared to consumer satisfaction research on other products, book-related studies are scarce. R.T. Tapushe found that information and website system quality most affect online news reader satisfaction [38]. D. Saxon et al. concluded from student learning outcomes that journal articles with hyperlinks improve reader satisfaction [39]. Zhang Feixiang found that satisfaction most affects consumer loyalty when studying book consumer loyalty [40]. Kuang Xia found that consumer satisfaction mediates the relationship between perceived quality and loyalty [41].

2.3 Literature Review Summary

As an important data source in the big data era, online reviews have been extensively studied and their commercial value greatly recognized. Online reviews provide the most intuitive, specific, and authentic consumer experiences, reflecting consumers' primary concerns, making them important resources for studying consumer satisfaction factors. Existing research has separately studied online review sentiment analysis and factors affecting online shopping consumer satisfaction, but no research has mined consumer satisfaction factors from online reviews. Therefore, this study uses JD.com's artificial intelligence book reviews as an example to mine factors affecting reader satisfaction from book online reviews, further exploring their influence patterns and degrees to provide theoretical foundations and actionable models for improving reader satisfaction.

3. Research Process and Results

3.1 Research Design

This study first uses a supervised Naive Bayesian classifier to identify online review sentiment, then employs unsupervised K-means clustering algorithm to find main dimensions involved in reader comments as satisfaction factors, and finally uses decision tree methods to map the mechanisms of how each factor influences reader satisfaction [Figure 2: see original paper].

3.2 Data Acquisition and Preprocessing

3.2.1 Data Acquisition “Artificial intelligence” has become a new focus of international competition, not only a strategic technology for the future but also a new engine for economic and social development. In JD.com’s 2018 book sales ranking under the “Computer and Internet” category, the top four books were all AI-related: “Python Programming: From Entry to Practice,” “The Beauty of Mathematics,” “Machine Learning,” and “Deep Learning.” Searching with “artificial intelligence” as the keyword yielded 64,294 related books, with 123 having over 1,000 reviews. Further observation revealed that reviews for similar books from the same publisher are integrated, so data collection was conducted by publisher, obtaining 53,217 review texts.

3.2.2 Data Preprocessing Online review texts are notoriously messy and poorly structured, requiring noise reduction before analysis. First, improper comments were modified or removed, such as converting traditional to simplified Chinese, deduplication, and removing English comments. After noise reduction, 38,237 comments remained for factor extraction. For machine learning, considering single-machine speed and learning effectiveness (requiring relatively balanced quantities of different sentiment reviews), 10,000 book reviews were sampled from the above based on multi-class sentiment balance principles. After manual screening to remove irrelevant comments, 9,729 comments remained as the basis for manual annotation, sentiment classification, and decision tree learning.

3.3 Data Analysis

3.3.1 Overall Review Text Polarity Classification To encourage readers to share shopping experiences, JD.com Book Mall awards “Jingdou” points for reviews exceeding a certain length. While this encourages sharing, it also leads some consumers to pad word counts with invalid evaluations. Although preliminary processing was conducted during data processing, mismatches between content and ratings still exist (see), partly due to inaccurate rating standards and reflecting that e-commerce platforms need improvement in designing review systems and guiding objective evaluations. Therefore, this study first analyzes the true sentiment of review texts. The sentiment analysis process is shown in [Figure 3: see original paper].

TABLE:1 shows examples of JD.com book online reviews where ratings don’t match content.

(1) Review Text Polarity Annotation. To verify text polarity classification accuracy, this study uses supervised machine learning. First, each review’s sentiment was manually annotated into three levels, assigned values 1, 2, and 3. Value 1 includes: entirely negative reviews; mixed positive/negative reviews where negative exceeds positive without extreme evaluations, or extreme negative exceeds extreme positive when extreme evaluations exist. Value 2 includes:

entirely neutral reviews; mixed reviews where positive exceeds or equals negative without extremes, or extreme positive exceeds extreme negative when extremes exist. Value 3 includes: entirely positive reviews; descriptions of book content only. Extreme evaluations refer to reviews containing strong degree adverbs like “very,” “extremely,” or “too.”

(2) Text Structuring. Review texts are typical unstructured data requiring structuring before deep analysis. Texts are segmented into words, then a co-word matrix is constructed, and finally digitized into word vectors. Currently widely used Chinese word segmentation software includes ICTCLAS from the Chinese Academy of Sciences, JIEBA, THULAC from Tsinghua University, and ANSJ. JIEBA is most widely used with high accuracy. This study uses the JIEBA package for structuring.

JIEBA is a general-purpose segmentation tool that cannot accurately segment different text types and topics, so segmentation effectiveness largely depends on custom dictionaries built for text characteristics and content. Reader reviews reflect shopping experiences with focused concerns and relatively clear emotional expressions. Emotional expressions have relatively fixed collocations. Drawing on Chen Shuo’s summarized part-of-speech templates for emotional words [42] (see), this study identifies emotional words in book reviews and manually screens them to form a custom dictionary for book reviews, improving segmentation efficiency and effectiveness.

TABLE:2 shows the part-of-speech templates for emotional words in book reviews.

Based on these templates, emotional word combinations in book review texts were extracted. Emotional words appearing more than 50 times were manually identified to form the study’s custom dictionary. High-frequency emotional words are shown in **TABLE:3**.

On the segmentation basis, a co-word matrix for book reviews can be constructed. Since different reviews contain different numbers of words, vectors exist in different dimensional spaces, requiring dimension unification. The final dimension equals the number of different words across all reviews.

(3) Sentiment Polarity Classification Algorithm Selection. With vast numbers of reviews, manual sentiment annotation of all texts is costly and impractical. This study uses supervised machine learning algorithms to learn from training set samples, then uses the trained model to predict test set sentiment, verifying algorithm effectiveness based on consistency between predicted and annotated values.

The Naive Bayesian algorithm is the most widely used classification algorithm, characterized by simplicity and efficiency. This study uses Naive Bayesian algorithm for sentiment classification. The Naive Bayesian classifier is based on Bayes’ theorem in statistics (Formula 1). According to Bayes’ theorem, for a

classification problem given sample feature x , the probability that sample belongs to category y is:

$$p(y|x) = \frac{p(x|y)p(y)}{p(x)} \quad (\text{Formula 1})$$

Here, x is a feature vector with dimension M . Assuming feature conditional independence and expanding according to the total probability formula, the above formula can be expressed as:

$$p(y = c_k|x) = \frac{\prod_{i=1}^M p(x_i|y = c_k)p(y = c_k)}{\sum_k p(y = c_k) \prod_{i=1}^M p(x_i|y = c_k)} \quad (\text{Formula 2})$$

The prior probability of category y can be calculated from the training set. Where $P(y = c_k)$ is the prior probability of class c_k . Assuming the training set contains Q samples, with class c_k containing N ($N < Q$) samples:

$$p(y = c_k) = \frac{N}{Q} \quad (\text{Formula 3})$$

Then, by statistics on the training set, the conditional probability of each feature in each class is estimated. $P(x_i|y = c_k)$ is the class-conditional probability of feature x_i in class c_k , referring to the probability of a feature appearing in a certain dimension of the sample feature vector under class c_k . Assuming c_k has R samples, and feature x_i appears r times in the n th dimension of the feature vector:

$$p(x_i|y = c_k) = \frac{r}{R} \quad (\text{Formula 4})$$

Since the denominator is total probability and can be considered constant, it need not be calculated.

(4) Classification Effect Evaluation Metrics. Machine learning model effectiveness can be evaluated through specific metrics, with the most classic being Accuracy, Precision, Recall, and F1-score:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (\text{Formula 5})$$

$$Precision = \frac{TP}{TP + FP} \quad (\text{Formula 6})$$

$$Recall = \frac{TP}{TP + FN} \quad (\text{Formula 7})$$

$$F1_score = \frac{2 \times Precision \times Recall}{Precision + Recall} = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (\text{Formula 8})$$

Where TP (True Positive): predicted positive, actual positive; FP (False Positive): predicted positive, actual negative; FN (False Negative): predicted negative, actual positive; TN (True Negative): predicted negative, actual negative. Accuracy is the most commonly used metric, reflecting overall recognition effectiveness; Precision reflects the “better to miss than misclassify” principle, showing how many predicted positive samples are correct—the higher the value, the stronger the model’s ability to identify positive samples; Recall reflects the “better to misclassify than miss” principle, also called “completeness,” showing the probability of true positives being identified; F1-score is the weighted average of precision and recall, with maximum value 1 and minimum value 0. Higher F1-score indicates more robust classification models.

(5) Classification Result Comparative Analysis. If a feature in the training set has never appeared (i.e., a word not present in the training set), its occurrence probability is 0. Using multiplication to calculate text probability would make the entire text probability 0, which is unreasonable. To avoid this, probability estimates typically use “Laplace smoothing ($\alpha=1$)” or “Lidstone smoothing ($0 < \alpha < 1$)” for correction. The smoothing coefficient is a “hyperparameter” that cannot be learned and must be set manually, ultimately selected based on evaluation metrics.

To achieve optimal classification, this study uses cross-validation to test various combinations of smoothing coefficient α (0.2, 0.4, 0.6, 0.8, 1.0), feature extraction methods, and stopword usage, selecting the best-performing combination.

The specific process for determining satisfaction factors is: review text segmentation (all reviews), using Word2Vec to train segmented texts, mapping each word to word vector space, then using K-means algorithm to cluster high-frequency nouns in word vector space. This segmentation focuses more on noun extraction, so besides building a custom dictionary, the stopword library needs multiple supplements to adapt to book review characteristics and improve segmentation accuracy. Part-of-speech tagging was then performed. Due to the huge vocabulary size, the constructed word vector space is high-dimensional and sparse, requiring dimensionality reduction. This study uses Word2vec for dimensionality reduction and word vector matrix construction for clustering analysis.

The K-means algorithm is an important unsupervised learning algorithm following the winner-take-all rule. Its main idea is to randomly select K centroids in a given dataset, form clusters around centroids, and through multiple distance calculations, ultimately minimize intra-cluster distances and maximize inter-cluster distances.

The final results show that when $\alpha=0.4$, using CountVectorizer for feature extraction without stopwords achieves the best learning effect, with learning accuracy reaching 82.8%. Other metrics are shown in **TABLE:4**.

TABLE:4 shows Precision, Recall, and F1_{score} for different sentiment classifications. The word cloud distribution of main high-frequency nouns is shown in [Figure 4: see original paper], where font size is proportional to word frequency (see **TABLE:5**). It can be seen that “content” is the core focus of readers, indicating that the main factor affecting JD.com reader satisfaction is book content. Meanwhile, quality, printing, speed, and price are also main factors affecting reader satisfaction.

For K value selection, observation locked the range between 2 and 9. The elbow method and silhouette coefficient were used to verify the number of clusters K. After multiple runs, the optimal K value was determined. The “elbow” position corresponds to K=6 [Figure 5: see original paper]. The silhouette coefficient results also show K=6 as optimal [Figure 6: see original paper]. Finally, through stepwise dimensionality reduction, [Figure 7: see original paper] was obtained. Through hierarchical clustering, six key factors affecting reader satisfaction were identified: packaging, logistics, and service related to third-party services, and price, content, and quality related to product attributes.

3.3.2 Determination and Quantification of Satisfaction Influence Factors (1) **Determination of Satisfaction Influence Factors.** Objectively identifying key factors affecting reader satisfaction from massive review texts is a core issue. Traditional satisfaction factors are based on previous research and verified through questionnaire analysis. However, in the big data era, obtaining research samples is more convenient and data more complete. Online reviews can be used to extract readers’ focus as satisfaction evaluation indicators [33,43-44]. High-frequency nouns in texts can serve as feature indicators [45] reflecting readers’ product concerns, i.e., satisfaction influence factors.

Currently, Python libraries provide two effective feature vector extraction methods: CountVectorizer, which considers word frequency in current training texts; and TfidfVectorizer, which considers both word frequency in current texts and occurrence in other training texts.

Stopwords are frequently occurring but semantically insignificant words like “的” (de), “在” (zai), “和” (he). After segmentation, high-frequency meaningless words were manually identified to expand JIEBA’s default stopword library. However, whether stopwords positively affect classification results requires experimental verification.

(2) **Quantification of Satisfaction Influence Factors.** User product evaluations and feedback mainly manifest as subjective evaluations and descriptions of feature words. Through observation and analysis of large review texts, this description structure can be summarized as “feature word + degree adverb + emotional word” or “feature word + emotional word.” For example, in “客服

小姐姐人很好，服务态度超级棒，很详细地为我介绍哪本书适合我，而且书的印刷清晰，物流也很快，必须五星好评！” (Customer service is great, service attitude is super good, detailed introduction of suitable books, clear printing, fast logistics, must give five stars!), three structures exist: “服务态度 + 超级 + 棒” (service attitude + super + great), “物流 + 很 + 快” (logistics + very + fast), and “印刷 + 清晰” (printing + clear). Therefore, evaluation index quantification uses feature words as axes, locating degree adverbs and emotional words within the interval [-u, u], then assigning values. Different text types have different u values; this study uses u=4. Partial degree adverb and emotional word assignments are shown in **TABLE:6**.

TABLE:6 shows assignments for degree adverbs and emotional words (partial).

Based on assignments, the score for feature word i is calculated as:

$$Score(i) = a \cdot word(i) \quad (\text{Formula 9})$$

Where a is the degree adverb score and $word(i)$ is the emotional word score describing feature word i .

In sentiment analysis research, some scholars propose the concept of valence shifters—words or phrases that may change sentiment orientation [43]. Common shifters are negation words; if negation words exist within the defined interval before or after feature words, they directly affect overall text semantics, forming polarity reversal. For example: “书的/内容/很/精彩” (positive) becomes “书的/内容/不/是/很/精彩” (negative) after adding negation. Therefore, the score for feature word i is:

$$Score(i) = (-1)^t \cdot a \cdot word(i) \quad (\text{Formula 10})$$

Where t determines whether polarity reversal occurs.

Based on this quantification method, each feature word’s score in each review was obtained. Specific scoring is shown in **TABLE:7**.

TABLE:7 shows partial examples of quantified review text feature words.

Finally, using each complete online review as a unit, sentiment scores for six feature types were aggregated to obtain a multi-dimensional data matrix of satisfaction influence factors.

3.3.3 Decision Tree Analysis of Reader Satisfaction Influence Factors

(1) Decision Tree Algorithm Selection. Decision tree methods extract classification rules in tree representation form from unordered, irregular sample datasets based on the natural states or conditions of decision problems, action plans, profit/loss values, and predicted results, reflecting the entire process of human thinking, prediction, and decision-making.

Decision tree learning typically includes three steps: feature selection, decision tree generation, and pruning. Decision tree generation mainly consists of three algorithms: ID3, C4.5, and CART, differing in information measurement methods, node feature selection, and branch numbers. ID3 and C4.5 use entropy to measure information uncertainty, while CART uses the Gini index. ID3 selects features with maximum “information gain,” C4.5 selects features with maximum “information gain ratio,” both being multi-way trees. CART is a binary tree.

Through recursive algorithms, decision trees continue calculating until they cannot proceed, easily causing overfitting. Pruning algorithms improve generalization and prevent overfitting, divided into pre-pruning and post-pruning. Pre-pruning evaluates each node before splitting during generation, stopping if splitting doesn’t improve generalization performance. Post-pruning first generates a complete decision tree from the training set, then examines non-leaf nodes bottom-up, replacing subtrees with leaf nodes if it improves generalization.

(2) Decision Tree Learning Results and Analysis. This study calls the decision tree algorithm from Python’s Sklearn library, using optimized ID3 algorithm with pre-pruning, with tree depth set to 4.

Randomly selecting 75% of the satisfaction influence factor and corresponding sentiment comprehensive evaluation multi-dimensional data matrix as the training set (satisfaction influence factors as x_{train} , comprehensive sentiment evaluation as y_{train}) and 25% as the validation set (x_{test} and y_{test}), the predicted result is y_{pred} . By comparing y_{test} and y_{pred} , the decision tree classification accuracy is determined to be 83.2%, with good classification effects. Other metrics are shown in **TABLE:8**.

TABLE:8 shows test results for the relationship between various influence factors and reader satisfaction.

FIGURE:8 shows the decision tree for all samples. Each internal node represents a test on an attribute, each edge represents a test result corresponding to “True” and “False” (left side is “True,” right side is “False”). The decision process starts from the root node, with each internal node using the influence factor with maximum information gain as the criterion. Test data is compared with feature nodes, selecting the next comparison branch according to results until reaching a leaf node as the final decision.

In the sample, negative, neutral, and positive reviews number 3,447, 2,836, and 3,446 respectively. Before analysis, the system entropy (uncertainty) is 1.5792. Calculating information gain for each factor, “content” has the greatest impact on reader satisfaction, meaning evaluation of content most reduces uncertainty about reader satisfaction.

For easier demonstration, based on book content scores, the decision tree is divided into two parts [Figure 8: see original paper]: the upper part for relatively satisfactory content (2,161 reviews), the lower part for content satisfaction scores below 1.5 (7,568 reviews).

For books with relatively satisfactory content (score above 1.5), as long as price is not too expensive (price score above -1.5), service level is average or above (service score above -0.5), and packaging is not too poor (packaging score above -1.5), 89.2% of evaluations are positive ($1,927/2,161 = 89.2\%$, path). Although the number of negative reviews is minimal for content-satisfactory books, attention is still needed. Price is an important factor affecting comprehensive evaluation results. If readers consider price very unsatisfactory (score below -3), final evaluations have no positive reviews regardless of other factors (). For other factors, even with low scores, readers give more neutral than negative reviews, as in processes and .

There are 1,964 reviews with content scores between 0.5 and 1.5 (content okay but not great) (). In this case, even with dissatisfaction in service, packaging, etc., the proportion of neutral reviews is high at 88.7% ($1,742/1,964 = 88.7\%$), but positive reviews are fewer than negative ones.

The highest number of reviews are for average or poor content (5,604 reviews). If packaging and book quality don't reach good levels, 58.8% ($3,298/5,604 = 58.8\%$) of comprehensive evaluations are negative. However, when packaging, quality, and price scores are high, a high proportion of readers remain satisfied (processes and).

For JD.com AI book readers, book content is the most critical factor affecting overall experience, with clear correlation between content feelings and comprehensive evaluation. AI field readers extremely value book content—when content is average or satisfactory, comprehensive evaluations basically match content sentiment. However, when content is unsatisfactory, readers are relatively tolerant and won't easily give negative reviews if other factors provide good experiences.

Under different content satisfaction levels, reader satisfaction decision processes differ. For books with good content, expensive price is the main factor causing negative reviews; service and packaging have minimal impact unless very poor; book quality and logistics have negligible impact. For books with okay or average content, readers focus more on service and logistics—if these aren't too poor, most sentiments are neutral, but positive reviews are fewer than negative ones. For books with average or poor content, if packaging and service quality don't reach high levels, most readers are dissatisfied; but high scores in packaging, quality, and price still yield high satisfaction proportions.

4. Conclusion

This study proposes a research model for reader satisfaction adapted to big data environments—combining machine learning and natural language processing methods to deeply mine main factors affecting reader satisfaction and how they influence it. The methods used have strong expandability, can automat-

ically extract product-specific satisfaction factors through continuous learning without content limitations, and can maximally reflect consumers' overall evaluations. Deep mining can identify problems in publishers' online book sales through online review analysis.

The study finds that Naive Bayesian algorithm achieves good sentiment classification with 82.8% accuracy, solving non-standardization and randomness issues in satisfaction evaluation to obtain relatively objective comprehensive evaluation scores. K-means clustering effectively selects main dimensions reflecting reader satisfaction. Decision trees intuitively reflect influence degrees and patterns of various factors on reader satisfaction.

For JD.com AI book readers, packaging, logistics, service, price, content, and quality are the key factors affecting satisfaction. Different content satisfaction levels lead to different satisfaction decision processes. Similarly, e-commerce platforms can use machine learning algorithms to continuously track and analyze historical online reviews for other products, extract main satisfaction factors for different product types, simplify review processes, design better evaluation systems, and guide reader reviews. This provides relative standards for readers, reducing evaluation difficulty and improving review data quality. Based on different influence patterns and degrees, merchants and platforms can focus on and improve specific factors to enhance consumer satisfaction.

References

- [1] Dangdang, Renrenshu. 2018 China Book Reading Market Special Analysis Report [EB/OL]. [2018-06-10]. http://www.sohu.com/a/245466602_{100218710}.
- [2] Analysys. China B2C Market Quarterly Monitoring Report Q3 2017 [EB/OL]. [2018-06-10]. <https://www.analysys.cn/article/analysis/detail/1000995>.
- [3] UTZ S, KERKHOF P, VAN D, et al. Consumers: how consumer reviews influence perceived trustworthiness of online stores [J]. *Electronic commerce research and applications*, 2012, 11(1): 49-58.
- [4] TAX S S, BROWN S W, CHANDRASHEKARAN M. Customer evaluations of service complaint experiences: implications for relationship marketing [J]. *Journal of marketing*, 1998, 62(2): 60-76.
- [5] PARK C, LEE T M. Information direction, website reputation and eWOM effect: a moderating role of product type [J]. *Journal of business research*, 2009, 62(1): 61-67.
- [6] JENSEN M L, AVERBECK J M, ZHANG Z, et al. Credibility of anonymous online product reviews: a language expectancy perspective [J]. *Journal of management information systems*, 2013, 30(1): 293-324.
- [7] LUDWIG S, RUYTER D, FRIEDMAN M, et al. More than words: the influence of affective content and linguistic style matches in online reviews on conversion rates [J]. *Journal of marketing*, 2013, 77(1): 87-103.
- [8] LI X, HITT L M. Self-selection and information role of online product

- reviews [J]. *Information systems research*, 2008, 19(4): 456-474.
- [9] XIAO S, WEI C P, DONG M. Crowd intelligence: analyzing online product reviews for preference measurement [J]. *Information & management*, 2016, 53(2): 169-182.
- [10] HODAC N N, CARSON S J, MOORE W L. The effects of positive and negative online customer reviews: do brand strength and category maturity matter? [J]. *Journal of marketing*, 2013, 77(6): 37-53.
- [11] WANG Junyi, YAN Qiang. Impact of online reviews on sales of search products with different popularity: taking JD.com mobile phones as an example [J]. *Chinese Journal of Management Science*, 2013, 21(S2): 406-411.
- [12] LEE J H, JUNG S H, PARK J H. The role of entropy of review texts sentiment on online WOM and movie box office sales [J]. *Electronic commerce research and applications*, 2017, 22: 42-52.
- [13] DUAN W, GU B, WHINSTON A B. Do online reviews matter? — an empirical investigation of panel data [J]. *Decision support systems*, 2008, 45(4): 1007-1016.
- [14] PENG Lihui, LI He, ZHANG Yanfeng, et al. Empirical research on factors influencing usefulness of online reviews based on brand reputation perception differences [J]. *Information Science*, 2017, 35(9): 159-165.
- [15] AHMED R R, SEEDANI S K, AHUJA M K, et al. Impact of celebrity endorsement on consumer buying behavior [J]. *Ssrn electronic journal*, 2015(16): 12-20.
- [16] KUMAR N, BENBASAT I. Research note: the influence of recommendations and consumer reviews on evaluations of websites [J]. *Information systems research*, 2006, 17(4): 425-439.
- [17] FLOH A, KOLLER M, ZAUNER A. Taking a deeper look at online reviews: the asymmetric effect of valence intensity on shopping behavior [J]. *Journal of marketing management*, 2013, 29(5-6): 646-670.
- [18] ZHAO K, STYLIANOU A C, ZHENG Y. Sources and impacts of social influence from online anonymous user reviews [J]. *Information & management*, 2018, 55(1): 16-30.
- [19] WANG Xuhui, ZHANG Qilin, DU Hang. Impact of online customer reviews on product sales: the moderating role of brand strength and product maturity [J]. *Journal of Industrial Engineering and Engineering Management*, 2018, 32(3): 9-18.
- [20] HEYMAN J, ARIELY D. Effort for payment: a tale of two markets [J]. *Psychological science*, 2004, 15(11): 787-793.
- [21] SWEENEY J C, SOUTAR G N, MAZZAROL T. Word of mouth: measuring the power of individual messages [J]. *European journal of marketing*, 2012, 46(1/2): 237-257.
- [22] SKOWRONSKI J J, CARLSTON D E. Negativity and extremity biases in impression formation: a review of explanations [J]. *Psychological bulletin*, 1989, 105(1): 131-142.
- [23] NING Lianju, SUN Han. Impact of online negative reviews on online consumers' purchase intention [J]. *Journal of Technology Economics*, 2014, 33(3): 54-59, 96.

- [24] SONG Yuanzheng. Impact of online negative reviews on consumers' purchase intention: the moderating role of product type [D]. Harbin: Harbin Institute of Technology, 2016.
- [25] CHEVALIER J, GOOLSBEE A. Measuring prices and price competition online: amazon.com and barnesandnoble.com [J]. *Quantitative marketing & economics*, 2003, 1(2): 203-222.
- [26] SUN Kelin, ZHANG Xinyue, LIN Yixia, et al. Impact of online reviews on commodity sales in e-commerce: taking Dangdang's self-operated books as an example [J]. *E-commerce*, 2018(2): 33-34.
- [27] JI Jingwei. Empirical research on the impact of online reviews on book sales [D]. Beijing: China University of Geosciences, 2018.
- [28] CARDOZO R N. An experimental study of customer effort, expectation, and satisfaction [J]. *Journal of marketing research*, 1965, 2(3): 244-249.
- [29] OLIVER R L. Measurement and evaluation of satisfaction processes in retail settings [J]. *Journal of retailing*, 1981, 57(3): 25-48.
- [30] OLIVER R L. A behavioral perspective on the consumer [J]. *Asia pacific journal of Management*, 1997, 2(2): 285-286.
- [31] HUNT H K. Consumer satisfaction: discussant comments [J]. *Advances in consumer research*, 1983, 10(4): 262-262.
- [32] MOEZZI H. Correlation between the determinants of customer relationship management system, electronic (e-CRM) customer satisfaction [J]. *Research bulletin*, 2009, 4(22): 25-12.
- [33] ZHANG Shengliang, LI Xiaodong. Research on factors influencing online shopping customer satisfaction [J]. *Journal of Tianjin University (Social Sciences)*, 2013, 15(2): 109-115.
- [34] ZHA Jinxiang, WANG Lisheng. Empirical research on factors influencing online shopping customer satisfaction [J]. *Management Science*, 2006, 19(1): 50-58.
- [35] ZHANG L, TAN W, XU Y, et al. Dimensions of perceived risk and their influence on consumers' purchasing behavior in the overall process of B2C [J]. *Lecture notes in electrical engineering*, 2012, 111: 1-10.
- [36] LI Yuping, HU Pei. Research on factors influencing customer online shopping satisfaction [J]. *Commercial Research*, 2015, 57(1): 160-165.
- [37] TANDON U, KIRAN R, SAHA. Analyzing customer satisfaction: users' perspective towards online shopping [J]. *Nankai business review international*, 2017, 8(3): 266-288.
- [38] TAPUSHE R T, IMRAN M, MOHAMED E H, et al. To read or not to read: modeling online newspaper reading satisfaction and its impact on revisiting intention and word-of-mouth [J]. *Journal of information, knowledge and management*, 2018, 13(3): 337-359.
- [39] SAXON D, PEARSON A T, WU P. Hyperlink-embedded journal articles improve statistical knowledge and reader satisfaction [J]. *Journal of graduate medical education*, 2015, 7(4): 654-657.
- [40] ZHANG Feixiang, YANG Yang, CHEN Jingliang. Empirical research on factors influencing book online consumer loyalty [J]. *China Business and Market*, 2014(11): 87-93.

- [41] KUANG Xia, YANG Yang. Empirical research on the impact of book online consumer perceived quality on loyalty [J]. Science-Technology & Publication, 2019, 4: 151-156.
- [42] CHEN Shuo. Mining product review features and emotional words based on part-of-speech and syntax [D]. Hebei: Hebei University, 2012.
- [43] WU Weifang, GAO Baojun, YANG Haixia, et al. Impact of review text on hotel satisfaction: a method based on sentiment analysis [J]. Data Analysis and Knowledge Discovery, 2017(03): 62-70.
- [44] XIA Mingshou. Data mining of post-purchase evaluation features based on buyer online reviews [J]. China Business and Market, 2017(7): 30-38.
- [45] LI Huifu, LU Guang. Research on text classification method based on multi-type classifier fusion [J]. Application Research of Computers, 2019, 36(03): 119-122.
- [46] HAN Zhongming, DUAN Dagao. Data Analysis and R [M]. Beijing: Beijing University of Posts and Telecommunications Press, 2014.

Author Contributions

Wang Yue: Proposed research ideas, designed research plan, collected, cleaned, and analyzed data, wrote and revised the paper.

Yin Lichun: Refined design ideas, analyzed data, wrote, reviewed, and revised the paper, finalized the manuscript.

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv — Machine translation. Verify with original.