Journal of the Operational Research Society

ISSN: 0160-5682 (Print) 1476-9360 (Online) Journal homepage: www.tandfonline.com/journals/tjor20

Consumer segmentation and pricing optimisation with online reviews: a sentiment analysis-based decision-making framework

Shiyu Liu, Zixu Liu, Jun Wang & Liwei Xu

To cite this article: Shiyu Liu, Zixu Liu, Jun Wang & Liwei Xu (26 Feb 2026): Consumer segmentation and pricing optimisation with online reviews: a sentiment analysis-based decision-making framework, Journal of the Operational Research Society, DOI: 10.1080/01605682.2026.2630957

To link to this article: https://doi.org/10.1080/01605682.2026.2630957

Published online: 26 Feb 2026.

JOURNAL OF THE OPERATIONAL RESEARCH SOCIETY
https://doi.org/10.1080/01605682.2026.2630957

RESEARCH ARTICLE

OPEN ACCESS

Consumer segmentation and pricing optimisation with online reviews: a sentiment analysis-based decision-making framework

Shiyu Liu[a*], Zixu Liu[b], Jun Wang[c] and Liwei Xu[d]

[a]University of Warwick, Coventry, UK; [b]University of Southampton, Southampton, UK; [c]Beihang University, Beijing, China; [d]Dongbei University of Finance and Economics, Dalian, China

ABSTRACT

With the development of online platforms and the continuous advancement of text analysis technologies, online reviews have become an important resource for retailers to understand consumer characteristics. In this paper, we provide a comprehensive decision-making framework for retailers based on online product reviews to conduct consumer segmentation and differential pricing. Existing research mainly focuses on extracting consumers' preferences for product quality dimensions from online reviews, with little attention given to the price preferences embedded in the text. Thus, this paper proposes a deep learning-based analysis method to extract consumer information on both price and quality sensitivities, aiming to capture consumer purchasing utilities and subsequently segment consumers along these two dimensions. Building upon the identified consumer segmentation and sensitivities within each segment, we establish a differential pricing model to maximise the retailer's profit. To verify the accuracy and feasibility of our proposed deep learning-based analysis method, we use real-world review data to train and test our model. The experiment results show competitive accuracy compared with the current works, which means our method could provide retailers with a new perspective and approach for analysing online reviews and conducting consumer segmentation. Furthermore, after the consumer segmentation, we continue to validate the effectiveness of the differential pricing model. Comparative experiments demonstrate that our pricing strategies based on both consumer price and quality sensitivities in different segmentations can enhance retailers' profitability. In conclusion, our framework provides retailers with theoretical support for implementing consumer segmentation and differential pricing strategies based on online reviews in e-commerce scenarios.

PRACTITIONER SUMMARY

The research question of this paper is to propose a novel decision framework to help retailers utilise consumer online review data to segment consumers based on price and quality sensitivity and subsequently implement differential pricing to maximise retailer profits. Existing works have not fully explored such additional information embedded in online reviews, which can play an important role in retailers' pricing decisions. In our framework, a DL (Deep learning)-based approach, particularly Transformer-based models, for sentiment classification is applied and experimented with. From a practical perspective, our study offers valuable management implications for retailers. Except for segmenting the consumers and proposing more effective differential pricing strategies to help decision-making for retailers to maximise their profit, our framework allows retailers to seamlessly integrate any Transformer-based NLP models based on their specific tasks and needs. Therefore, in real-world business scenarios, retailers can apply our method to segment target consumers and identify the characteristics of consumers within each segment, assisting further decision-making. Furthermore, we provide several references and insights into retailers' differential pricing strategies. All of these enhance the practical applicability of our proposed framework, making it suitable for direct use by retailers in real-world scenarios.

ARTICLE HISTORY
Received 3 July 2025
Accepted 7 February 2026

KEYWORDS
Online review; consumer segmentation; differential pricing; deep learning; sentiment analysis

1. Introduction

Due to the rapid expansion of big data analytics, companies can now collect various consumer behaviour data, enabling them to adjust prices accordingly (Li et al., 2023). When firms have information about consumers' previous purchases, they can analyse the data to identify consumers and offer different prices with different characteristics (Fudenberg & Villas-Boas, 2006; Li et al., 2023; Xu et al., 2025), which is referred to as the "Behaviour-Based Pricing" policy (BBP) with consumer recognition. The BBP policy has been a common pricing policy across various industries, including retailing. Retailers can enhance their profitability by setting different prices for different consumer segments. For example, on popular retail platforms like Amazon and Taobao, retailers analyse

CONTACT Zixu Liu zixu.liu@soton.ac.uk Southampton Business School, University of Southampton, Southampton, UK, SO17 1BJ
*Present affition: Petrochina (Beijing) Digital Intelligence Research Institute Co., LTD., Beijing, China

consumers' shopping behaviours to selectively offer discounts or vouchers tailored to different preferences. In existing research on BBP policy, consumer recognition primarily focuses on the consumer's purchasing behaviour, such as whether they are new users or repeat consumers (Jing, 2017; Li et al., 2024), or which firm they buy from in a competitive setting (Wang et al., 2023; Wang & Ng, 2020). However, this method overlooks the underlying reasons behind consumer purchase decisions, such as the impact of consumer characteristics, which will further impact the retailers' pricing decisions. Therefore, the accurate identification of consumers and the implementation of efficient differential pricing have become a crucial issue for retailers.

With the rapid development of online retail platforms, an increasing number of consumers are opting for online shopping and are willing to provide online reviews for the products they purchase (Bi et al., 2019; Chong et al., 2017). With current digital transformation technologies such as the Internet of Things and Cloud Computing, more powerful computer resources are provided to support the online platforms to host advanced data analytical models or algorithms (i.e., deep learning models). Under such a framework, consumer reviews not only provide additional information for other consumers' shopping decisions but also become a crucial information source for retailers to understand consumers (Xiao et al., 2016). In existing studies, consumer recognition based on online reviews largely focuses on consumers' ratings or attitudes towards products or product quality features (Ng & Law, 2020; Park, 2023; Wu & Liao, 2021) and assists in decisions on product rankings (Qin et al., 2024; Wu et al., 2024; Yin et al., 2023; Zheng et al., 2025) or product development (Joung & Kim, 2023) accordingly. However, existing literature has not fully explored the additional information embedded in online reviews, such as consumer price sensitivity, which can play an important role in retailers' pricing decisions. Motivated by this existing gap in the literature, we propose our first research problem: How to mine and interpret consumer consumption preferences, such as price sensitivity and quality sensitivity, from their online reviews? To address this question, we apply text mining techniques to extract meaningful information from online reviews. Specifically, as detailed in in Section 3, we employ Deep learning (DL) models to tackle sentiment classification as an effective method for determining the sentiment of each consumer's online reviews. We collect a substantial amount of review texts from Amazon within a chosen product category to serve as the training dataset for a Deep Learning-based (DL-based) sentiment classification model, which ensures the feasibility of training and the high accuracy of results.

Drawing on this wealth of information, consumer segmentation based on characteristics derived from online reviews becomes a key point of research. Consumer segmentation is a strategic and effective marketing strategy that aims to classify consumers into several groups and then support the marketing strategies (Wind & Cardozo, 1974). This approach enables retailers to implement differential pricing strategies, capitalising on the unique features of each consumer segment to optimise and maximise their profits (Lii & Sy, 2009; Raza, 2015; Yelkur & DaCosta, 2001). Previous studies have explored consumer segmentation and pricing strategies from various perspectives. For example, Fu et al. (2017) clustered players of a game based on engagement, performance, and social interactions, while others have focused on price sensitivity as a key indicator of consumer behaviour (Han et al., 2001). Recent work also highlights the importance of quality-related factors in shaping purchasing decisions. Liu et al. (2024) found that most review-derived features relate to product quality, and Chaerudin and Syafarudin (2021) provided empirical evidence that quality has a significant positive impact on purchase decisions. More importantly, Zhao and Peng (2023) found that the single dynamic quality competition strategy will always decrease the profits of the firms and the single dynamic price competition strategy only increases the profits of the rival firms with a large potential market size. The hybrid dynamic competition strategy combines these two dimensions and is more likely to get more profit for the firms. However, existing research rarely integrates consumer-perceived price and quality dimensions extracted from online reviews into segmentation and pricing decisions. Thus, building on the first research question, the second research problem in this paper is: How to segment consumers and implement differential pricing based on consumer price sensitivity and quality sensitivity? What is the value of this pricing strategy? To address this problem, we first extract review-based scores related to price and quality through text mining, and then estimate consumers' sensitivities using a linear regression pooling method. Based on their relative levels of price and quality sensitivity, consumers are classified into four distinct segments. Guided by these segment characteristics, we formulate an optimisation model to determine the optimal differential pricing strategy that maximises retailer revenue. The methodological details and the modelling framework are presented in Section 4. In addition, we conduct a case study to compare the performance of our model with that of a uniform pricing strategy, thereby evaluating the effectiveness and value of the differential pricing strategy.

Accordingly, this study makes the following key contributions:

- We extract two key consumer preference dimensions, price sensitivity and quality sensitivity, from online reviews, providing theoretical insights into consumer behaviour.
- We introduce a DL-based sentiment classification approach to effectively process original review texts and achieve high accuracy in extracting these consumer preferences by optimising score and label assignment, representing a methodological contribution in handling unstructured textual data.
- Based on the extracted consumer preferences, we propose a comprehensive pricing decision-making framework that integrates consumer segmentation and differential pricing and offers actionable guidance for retailers.

The rest of the article is organised as follows. Section 2 provides an extensive review of related literature. Section 3 depicts the details of our proposed approach for consumer segmentation based on online reviews. In Section 4, we establish an optimisation model for the differential discount pricing based on the consumer segmentation obtained in Section 3. Experiments and a case study are presented in Section 5 to illustrate how to apply consumer segmentation and differential pricing based on online reviews. Section 6 concludes the article and presents the management implications.

2. Literature review

This section reviews the relevant literature in three related streams: consumer segmentation based on online reviews, pricing methods based on online review information, and differential pricing strategies.

2.1. Consumer segmentation based on online reviews

With the increasing availability and abundance of online review data, online reviews have become a valuable source for analysing consumers' evaluations and attribute-related preferences (Ahani et al., 2019; Gao et al., 2024; Joung & Kim, 2023; Liu et al., 2019; Pandey et al., 2023). A growing body of literature exploits online reviews and other forms of user-generated content to infer consumer preferences by analysing post-consumption experiences and satisfaction. Although online reviews are generated after purchase, they encode rich information about experienced utility and satisfaction that can be systematically transformed into signals characterising consumer preference structures.

For example, Ahani et al. (2019) collected overall ratings and attribute-level ratings of hotels from TripAdvisor and applied a Self-Organising Map (SOM) to cluster consumers based on their satisfaction levels across multiple criteria, thereby identifying four distinct consumer segments. Similarly, Liu et al. (2019) developed psychographic lexicons to quantify consumer and item characteristics from online reviews and performed psychographic segmentation using density-based spatial clustering of applications with noise (DBSCAN). Other studies focus on extracting experiential and sentiment-based signals from review text to reveal latent preference structures. Pandey et al. (2023) utilised Latent Dirichlet Allocation (LDA) to identify experience dimensions in restaurant reviews and employed SentiStrength to quantify sentiment intensity. Consumer segments were then derived by clustering sentiment scores associated with each extracted topic. Joung and Kim (2023) further proposed an interpretable machine-learning framework that segments consumers based on the importance they assign to different product features.

More recent work has moved beyond coarse sentiment measures to capture fine-grained and item-specific preference signals. Liu et al. (2024) proposed a combined fine-grained sentiment analysis approach to uncover consumers' nuanced sentiment preferences towards specific product attributes. In a related vein, Gao et al. (2024) introduced a Gaussian personalised recommendation optimisation criterion to learn user preferences from user–item interactions, enabling recommendation models to adapt to preference variation across different items.

However, most existing studies leveraging online reviews focus on identifying which attributes consumers mention positively or negatively, thereby capturing their general preferences over product features. In these studies, price and quality are usually treated as product attributes, and consumer segmentation is based on differences in general preferences or attribute importance. In contrast, our study shifts the focus from preference to sensitivity. We examine how strongly consumers react to price- and quality-related information and use these reactions to characterise differences in consumer behaviour for segmentation.

2.2. Pricing based on online reviews

With the increasing availability of online review data, how to make more effective pricing decisions based on reviews has received growing attention in the literature.

A number of studies have demonstrated that online reviews can influence pricing decisions.

Kostyra et al. (2016) investigated the impact of online consumer reviews on consumers' consideration of brand, price, and technical product attributes. Feng et al. (2019) developed an analytical model and empirical framework to show how firms dynamically adjust prices based on online reviews. Duan et al. (2022) used a three-stage least squares model to estimate the effects of online reviews and coupons on online product sales and price in response to review sentiments across different product types. Zhao et al. (2022) analysed how online reviews affect pricing strategies under duopoly competition using a dynamic game-theoretic model. Zhao and Peng (2023) developed game-theoretic models to examine the effect of review volume and valence on different pricing strategies.

Then, more recent studies have concentrated on developing pricing strategies directly based on online reviews. Cai et al. (2018) analysed pricing strategies in a multi-manufacturer supply chain based on online reviews. Zhao and Zhang (2019) developed a dynamic programming model to jointly optimise service quality and pricing decisions under the influence of online reviews, showing that review-driven strategies lead to higher quality and pricing levels, particularly in consumer-intensive service systems. Zhang et al. (2021) investigated the frill and price decisions for a competitive e-market with online reviews. Guo et al. (2022) developed dynamic pricing strategies based on consumer learning from first- and third-party online reviews. Yan and Han (2022) developed pricing strategies based on online reviews in a remanufacturing context, considering both quality and experience dimensions. Yang and Zhang (2022) proposed a stochastic joint pricing and inventory model where the optimal policy depends on aggregate consumer ratings, revealing a trade-off between short-term profit maximisation and the generation of future demand through favourable reviews. Shin et al. (2023) studied the dynamic pricing strategy of a monopolist under social learning dynamics of consumers who use online reviews to estimate the quality of the product and developed a fluid approximation model to capture how consumer willingness to pay evolves with perceived quality. Wu et al. (2023) employed a Proximal Policy Optimisation algorithm to derive pricing strategies based on quality- and value-based online reviews.

2.3. Differential pricing strategy

In this subsection, we review the existing literature on differential pricing strategies and conduct a comparative analysis.

In economics, the act of establishing varying prices for an identical good is termed price discrimination (Varian, 1989). Extensive literature explores price discrimination from various perspectives, including price discrimination across different channels (Fu et al., 2021; Zhou et al., 2020) and across various consumer segmentations (Raza, 2015; Teimoury et al., 2020). In this paper, we focus on price discrimination across different consumer segments, which are recognised through consumers' online review texts and also involve consumer recognition. This type of price discrimination is known as behaviour-based price discrimination (Fudenberg & Villas-Boas, 2006).

In the existing literature on behaviour-based price discrimination, articles often achieve consumer recognition by assuming the distribution of consumer characteristics and employing a two-period model (or multi-period) to collect consumers' purchase history records or sales observations. Jing (2017) considered the consumer difference in quality valuation in a two-period vertical duopoly, and the retailer sets distinct prices for repeat consumers and the consumers purchasing in competitors previously. Colombo (2018) developed a behaviour and characteristic-based discriminatory pricing model, in which consumers exhibit heterogeneity in tastes and price sensitivity. In this study, consumer tastes are identified from the purchase history and the price sensitivity is related to the consumers' income. Bonatti and Cisternas (2020) aggregated consumers' purchase histories into scores and conducted price discrimination based on the scores. Ban and Keskin (2021) researched personalised dynamic pricing problems based on consumers' characteristics related to demand. Wang et al. (2023) studied the choices of uniform pricing or behaviour-based price discrimination in a two-period duopoly market. Zhang et al. (2023) investigated the behaviour-based price discrimination problem in a dual-channel supply chain, where consumers are heterogeneous in channel preferences. Table 1 summarises the literature review on behaviour-based price discrimination.

In summary, consumer recognition and segmentation in behaviour-based price discrimination studies are primarily based on the history of purchasing behaviours and are mostly limited to a single period. However, identifying consumers solely based on one-period purchase behaviour or sales records is not accurate enough. A comparative analysis of such works and ours is conducted in Table 1. Therefore, to fill the identified gaps, we expand the approaches and data sources for behaviour-based pricing. Compared to focusing on consumers' purchasing behaviours, our paper places greater emphasis on the reviews provided by consumers after making a

Table 1. Summary of literature review on behaviour-based price discrimination.

Paper	Discrimination dimension	Recognition source
Jing (2017)	Repeat or new buyer	Purchase behaviour in the first period
Colombo (2018)	Consumer tastes and price sensitivity	Purchase behaviour in the first period
Bonatti and Cisternas (2020)	Consumer scores on profitability, health risk,job security, or credit worthiness	Purchase behaviour in the first period
Zhou et al. (2020)	First-time or repeat buyers	Purchase behaviour in the first period and consumer income information
Ban and Keskin (2021)	Consumers' characteristics related to demand model	Sales observations over several selling periods
Wang et al. (2023)	Consumers subscribed to different firms	Purchase behaviour in the first period
Our paper	Consumer price and quality sensitivity (**Advantage**: significant impact on consumer purchase utilities)	Online review text data (**Advantage**: readily accessible and abundant with various consumer information)

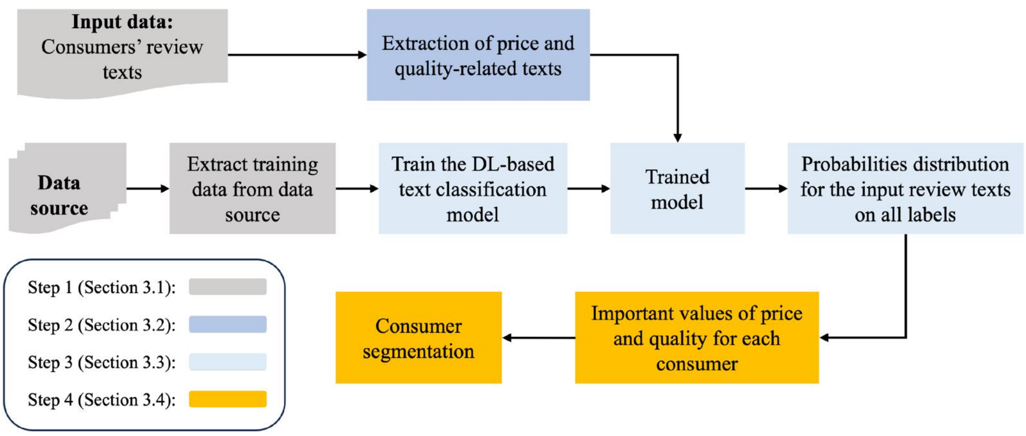

Figure 1. Proposed DL-based consumer segmentation approach.

purchase. With the development of online platforms, not only is online review data easily accessible, but it is also abundant. This presents an opportunity for more accurate consumer recognition and segmentation, and results in more optimal differential pricing strategies to attain higher profits.

3. Consumer consumption preferences analysis based on online reviews

In this section, we introduce the process of a deep learning-based consumer segmentation approach using online product reviews, as illustrated in Figure 1.

3.1. Data collection

In this study, we use reviews from the Amazon platform as an example to conduct sentiment analysis. The data we used were sourced from Ni et al. (2019), encompassing reviews from May 1996 to October 2018. This data source contains 233.1 million reviews and 15.5 million products. Our data sources consist of two types of files: review data and product metadata. Samples of review data and metadata are shown in Table A2 and Table A3. The data format employed here presents one review per line in JSON format, making the data easily human-readable. The entire process of data collection is illustrated in Figure 2.

We use the "category" field to match our search terms and obtain the products" "asin" (Amazon Standard Identification Numbers) in the product metadata. Subsequently, using "asin", we can retrieve all reviews for that product and extract the "overall", "reviewText", "reviewTime" and "reviewerID" to establish our basic data. Based on the extracted data, we initially conducted a "reviewerID" count, obtaining the cumulative review count for each consumer in the selected category, referred to as n_c. Next, to ensure that the selected reviewers are representative, we set a threshold, N. Since repurchase intention varies across different product categories, the value of N can be adjusted based on the category. Subsequently, the extracted data is divided into two parts: reviewers with $n_c \geq N$, along with all their reviews, will be collected as the input dataset, and the remaining consumer reviews can be used as training data for the text classification model. After extracting feature texts from the input dataset as described in Section 3.2, we can feed these extracted texts into our trained text classification model in Section 3.3 to obtain a probability distribution across all labels.

The main reason for adopting this data-splitting method is to keep the trained model in the same domain (under the same category) as the price and quality-related feature texts. Following the work of Liu et al. (2024), we utilise the same trained model for sentiment classification, similar to transfer learning. In our approach, we think that the model acquires robust prior knowledge during training on the training dataset. Once the training is complete,

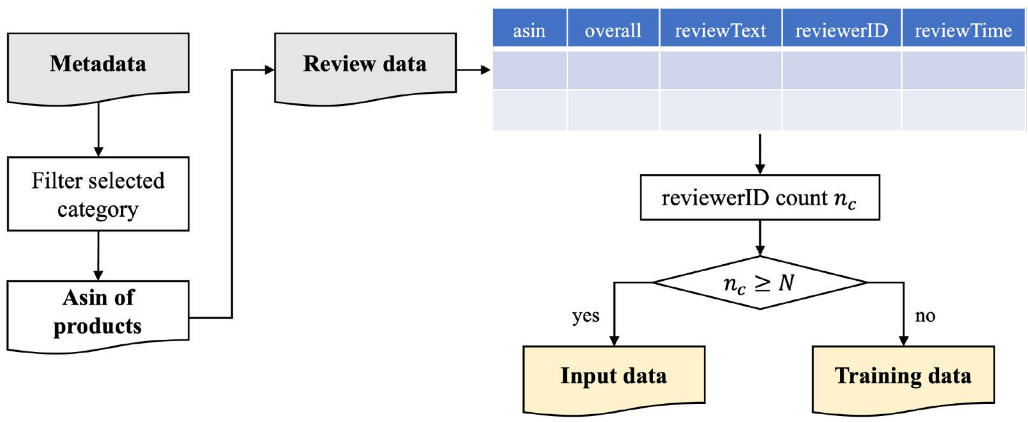

Figure 2. Process of data collection.

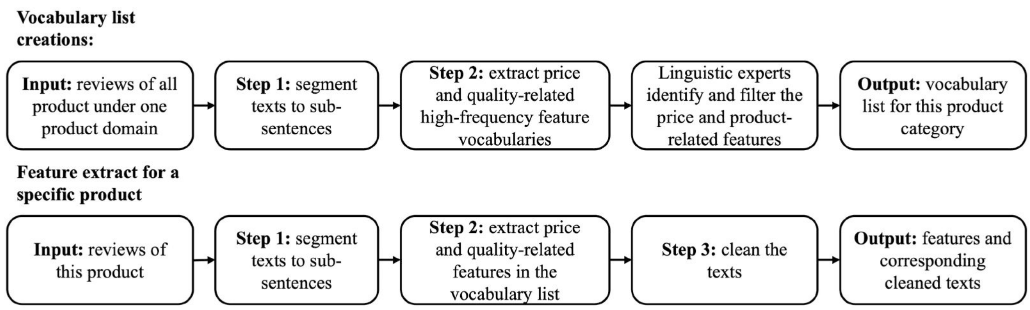

Figure 3. Process of product feature extraction.

we can directly apply the model to perform sentiment classification on the extracted texts from the input dataset without the need for additional feature-specific training.

3.2. Extraction of price and quality-related text from online reviews

Online reviews contain abundant textual information that reflects consumers' attitudes towards both price and quality. However, such information is often embedded in unstructured text and cannot be directly used for quantitative analysis. To address this issue, we extract price and quality-related textual features from online reviews and further use them to quantify consumers' sensitivity along these two dimensions, which subsequently enables consumer segmentation.

In order to fully preserve the quality and price texts as well as sentiment tendencies present in consumer reviews, we employed an NLP-based method. This method selectively extracts text related to quality and price-related features, while eliminating other information. The proposed method is depicted in Figure 3. The detailed steps of this method are explained as follows:

Step 1: Separate each review into subsentences with an index, indicating which sentences it belongs to.
Consumer reviews may include different sentiment tendencies for multiple features (e.g., quality and price). Therefore, we first divide each review into subsentences, aiming to include only one feature in each clause as much as possible. Specifically, consumer reviews typically constitute complete paragraphs that, in addition to describing price or quality features, may contain some extraneous text and information. When performing sentiment analysis for quality and price-related features through text classification, this redundant information can potentially introduce noise that impacts the final classification results and accuracy.

Step 2: Extract the price-related and quality-related features.
Our analysis of review texts is aimed at identifying consumers' sensitivities to quality and price. As such, we need to extract text related to price and quality-related features from online reviews for further analysis. To ensure precise extraction of relevant information, we first establish price-related and quality-related vocabularies (see Notes 2 and 3 for details). Yu et al. (2023) found that representing overall emotions through discrete emotions by constructing a domain-specific emotion lexicon yields higher prediction accuracy than valence or latent emotion variables generated by topic modelling. Inspired by this, we adopt a domain-specific approach to construct vocabularies that accurately capture price- and quality-related aspects from review texts. Since price-related

vocabulary generally exhibits a certain degree of stability and is independent of product categories, we develop a comprehensive and general vocabulary of price-related terms that contains both nouns and adjectives. However, vocabulary related to quality is closely tied to the category of products. Therefore, when constructing a vocabulary list of quality-related terms for products, specific analyses of reviews pertaining to each product category are required. The process of the build of vocabulary starts from some of the basic words of price- and quality-related recommendations by the linguistic experts, such as expensive, costly, and exceptional (Liu et al., 2024). Then the review data sets of the same domain reviews (in our case online product) are pre-processed, tokenised all subsentences to words, and the Porter stemming algorithm is used to reduce these words to their root form. Then use the ROUGE metric (Lin, 2004) to calculate the average similarity of these words to the price- and quality-related vocabularies, respectively. The words with higher values of the average similarity are added to the vocabulary.

Note 1: In NLP, the contiguous sequence of items such as words, letters, or symbols is called n-grams. To efficiently extract quality-related terms from the review texts, we keep noun and adjective words and then use a 2-gram approach to avoid missing product attributes in the quality dimension. The reason for this is that almost all features extracted for product ranking are nouns from the aspect of semantics (Liang et al., 2020; Liu et al., 2024; Wu & Liao, 2021). To enhance the accuracy and efficiency of feature extraction, all words are converted to lowercase. Additionally, we employ the Porter stemming algorithm (Van Rijsbergen et al., 1980) to reduce words to their root form. During this process, some sentences should be removed if they do not contain any nouns or adjective words.

Note 2: To match the product and price-related features with the pre-built vocabulary, we utilise the bag-of-words and term frequency-inverse document frequency (*tf-idf*) algorithms to transform words into sparse feature vectors. This could help us filter out the feature words included in pre-built vocabulary with lower frequency from the review documents, or add the feature words to the pre-built vocabulary that have a higher frequency.

Note 3: To better build a price-related and quality-related vocabulary, for a specific product domain, we extracted all frequency features above a certain threshold from all the reviews by using steps 2. Then the linguistic experts are invited to manually identify the price and product-related features and create a feature corpus for this product. Once the corpus is created, it can be used as a vocabulary list to automatically select useful price and quality-related feature words and filter out related words for similar products (in the same product subcategory) without the extra need for experts' involvement.

Step 3: Clean the text by matching the vocabulary with reviews.

Based on the price-related and quality-related vocabularies and the tokenised sentences obtained in Step 2, we clean the review texts by retaining those sentences that contain high-frequency price and quality-related features from the original review text. Then, we obtain indices for the sentences that contain specific words by referencing the segmented sentence list. For the feature sentences from the same review, we integrate the sentences that match price-related vocabulary and quality-related vocabulary separately (e.g., Table A1). The revised review texts are then used as input for our trained text classification model, which provides probability distributions among all labels.

3.3. DL-based classification model

Processing large datasets efficiently remains a key challenge in sentiment analysis. Deep learning models offer robust learning capabilities and can automatically extract meaningful features from raw text data without requiring intricate pre-processing steps (Cai et al., 2018). Additionally, they can effectively handle issues such as data sparsity and high-dimensional feature spaces, leading to better prediction accuracy (LeCun et al., 2015). Therefore, this section presents how we utilise the dataset to train a DL-based sentiment classification model.

Many online shopping platforms request consumers to provide ratings on a scale of 1 to 5 when they submit reviews (unlike online platforms for products, online service platforms, such as Airbnb, require consumers to provide ratings across several specified dimensions and the final score is then calculated as the average of these multiple ratings), so the sentiment words in text reviews are typically classified into three categories "negative", "neutral", "positive" or five categories "very negative", "negative", "neutral", "positive", "very positive". These labels could provide a reasonable sentiment tendency description for online reviews that can link with the rating scores 1–5 based on the method proposed by Liu et al. (2024). Thus, to enhance prediction accuracy and training efficiency, re-labelling the training review texts is essential (Liu et al., 2024). In this context, it is imperative to map all rating labels to the corresponding sentiment labels before training the model.

In our approach, following the comparative analysis of various classifiers by Liu et al. (2024), we select the Transformer as the classifier and use the training dataset extracted in Section 3.1 to train it. Introduced by Vaswani et al. (2017), the Transformer is a pioneering neural network architecture recognised for its self-attention mechanisms, facilitating effective modelling of global dependencies. The Transformer has been widely applied in Natural Language Processing and has exhibited commendable performance.

During the model training process, we use the training dataset extracted in Section 3.1 to train the classifier. Before training, the dataset is pre-processed to balance the label distribution to avoid the misleading appearance of a highly accurate model caused by class imbalance (Wang et al., 2021). Then, the balanced dataset is split into training, validation, and test datasets to evaluate the performance of the trained model. The validation dataset serves the purpose of offering an impartial evaluation of the model's performance during training and for fine-tuning the model parameters. Conversely, the test set is used when the model has undergone full training to evaluate its performance on entirely novel, unseen data. Then, we apply the trained text classification model to conduct the sentiment analysis for the input price-related and quality-related texts obtained in Section 3.2 to predict the probability distributions across the labels.

4. Consumer segmentation and differential pricing

Based on the data processing and training of the DL-based sentiment classification model as outlined above, we can extract consumers' sentiment tendencies in price and quality-related text on a category of products. In this section, we will leverage this information to further explore consumer preferences and categorise them along two dimensions: price and quality.

4.1. Consumer segmentation

For each review of each reviewer, we integrate the price-related and quality-related sentences separately. With the trained model in Section 3.3, we can predict the probability distribution of the extracted feature texts in each review. Subsequently, we calculate the sentiment score for price-related features $pr_{c,m}$ and quality-related features $qr_{c,m}$ for the m-th review of consumer $c \in \{1, 2, \ldots, C\}$ by assigning numerical values to each sentiment class (e.g., negative $= -1$, neutral $= 0$, positive $= 1$), and then multiply these values by the probabilities of each class as follows:

$$\begin{cases} pr_{c,m} = -1 * neg^{pr}_{c,m} + 0 * neu^{pr}_{c,m} + 1 * pos^{pr}_{c,m} \\ qr_{c,m} = -1 * neg^{qr}_{c,m} + 0 * neu^{qr}_{c,m} + 1 * pos^{qr}_{c,m} \end{cases} \tag{1}$$

If a review does not contain quality-related or price-related text, we consider the consumer to have a neutral sentiment towards it. Therefore, the sentiment vector for the m-th review of consumer c is two-dimensional $\{pr_{c,m}, qr_{c,m}\}$, representing the sentiment scores obtained from the two types of text inputs fed into the trained model. Meanwhile, there is an overall score or the m-th review of consumer c (e.g. the rating score on the website), denoted as $sr_{c,m}$.

Numerous studies have demonstrated the relationship between overall consumer satisfaction and feature-specific satisfaction (Bi et al., 2019; Chaerudin & Syafarudin, 2021; Ghali-Zinoubi & Toukabri, 2019). Thus, we utilise linear regression to obtain parameters for each consumer, following the approach adopted in Yang et al. (2021). However, it is important to note that there is no model universally suitable for all data and consumers (Ding et al., 2018). Thus, to better capture the distinct characteristics of each consumer, we develop a model selection method that includes a pool of linear models to achieve the optimal fit for each consumer. The regression and model selection process is depicted in Figure 4. During the process, we input the overall score extracted from each consumer review $sc_{c,m}$ as the dependent variable, while the scores related to price and quality $\{pr_{c,m}, qr_{c,m}\}$ serve as independent variables. The linear model pool includes basic linear regression, Ridge regression (McDonald, 2009), Lasso regression (Ranstam & Cook, 2018), Elastic Net regression (Ogutu et al., 2012) and Partial Least Squares regression (Geladi & Kowalski, 1986). Basic linear regression is the most widely used and simple model but may lead to overfitting. Compared to basic linear regression, ridge regression introduces regularisation to mitigate multicollinearity, while Lasso regression adds sparsity to coefficients, aiding in feature selection. Elastic Net regression combines L1 and L2 regularisation, allowing it to balance the characteristics of both Ridge (L2) and Lasso (L1) regression methods. Partial Least Squares regression reduces dimensionality by finding latent variables that explain variance in both predictors and may perform better on small-sample datasets. As different products and consumers may have unique characteristics, employing model selection allows for better fitting of the distinct features of each product and consumer.

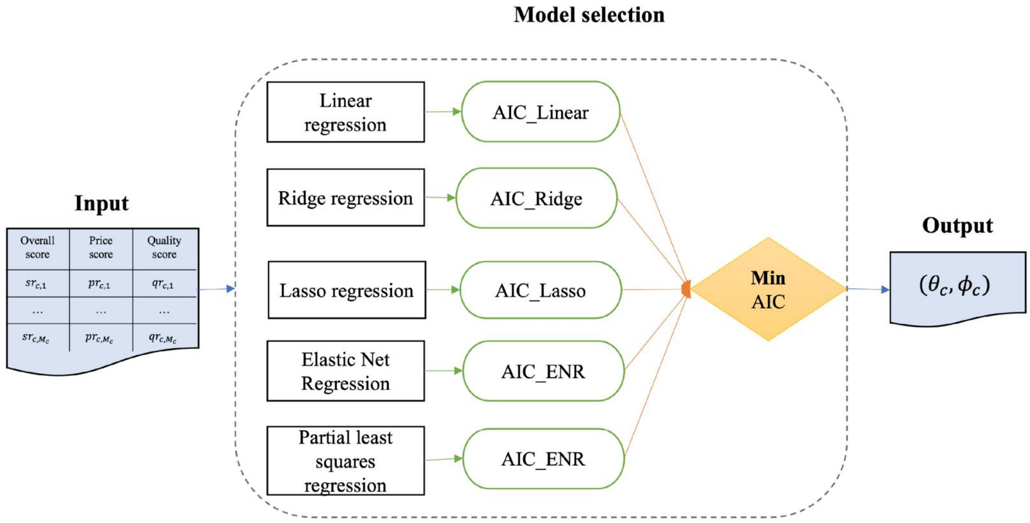

Figure 4. Process of regression and model selection.

During the model selection process, we use the Akaike information criterion (AIC) as the model selection criterion, which is a metric for evaluating the relative quality of different models. It balances a model's fit with its complexity, allowing for model comparison while applying a penalty to discourage overfitting. Introduced by Akaike (1987), the AIC stands as the most widely used model selection criterion (Cavanaugh & Neath, 2019). A smaller AIC value indicates a better fit of the model. Therefore, for each consumer, we select the fitting model with the smallest AIC value and obtain the fitted parameters as the price sensitivity θ_c and quality sensitivity ϕ_c.

Based on the consumers' price and quality sensitivities obtained above, we can then classify consumers into four distinct segments across the two dimensions. In order to facilitate comparability and differentiation, we normalised the price and quality sensitivities for all consumers using the Min-Max normalisation method, which normalises data by applying linear transformations to ensure balanced value comparisons between data points (Saranya & Manikandan, 2013). The normalised price sensitivities $\hat{\theta}_c$ and quality sensitivities $\hat{\phi}_c$, for consumer c are computed as follows:

$$\hat{\theta}_c = \frac{\theta_c - \min(\theta_1, \theta_2, ..., \theta_C)}{\max(\theta_1, \theta_2, ..., \theta_C) - \min(\theta_1, \theta_2, ..., \theta_C)} \quad (2)$$

$$\hat{\phi}_c = \frac{\phi_c - \min(\phi_1, \phi_2, ..., \phi_C)}{\max(\phi_1^q, \phi_2^q, ..., \phi_C^q) - \min(\phi_1^q, \phi_2^q, ..., \phi_C^q)} \quad (3)$$

Therefore, we segment consumers into four groups based on price and quality dimensions, assuming 0.5 as the cut-off value for both price and quality sensitivity divisions. Thus, we can obtain four segments of consumers: low-quality sensitivity-low price sensitivity ($s_1 = lqlp$), low-quality sensitivity-high price sensitivity ($s_2 = lqhp$), high-quality sensitivity-high price sensitivity ($s_3 = hqhp$) and high-quality sensitivity-low price sensitivity ($s_4 = hqlp$).

Then, to capture the characteristics of price and quality sensitivity within each segment, we sample consumers with notably high repurchase rates in the product category and collect their historical review data. These consumers embody the target consumer group for this product category, effectively representing diverse price and quality sensitivities across various consumer segments. Their distribution across the four segments also reflects, or closely approximates, the natural segmentation of all consumers in this category.

To provide more precise quality and price sensitivity attributes of each consumer segment, we introduce a credibility weighting factor, denoted as w_c, determined by the frequency of repurchases (i.e., the number of reviews in the selected category) by individual consumers. This factor serves to represent the reliability of consumer characteristics, and its calculation formula is as follows:

$$w_c = \begin{cases} 1 & \text{if } M_c \geq M^* \\ e^{M_c - M^*} & \text{if } M_c < M^* \end{cases} \quad (4)$$

where M^* represents the credibility threshold. We consider that when a consumer has written at least M^* reviews within a product category, their quality and price preferences can be reliably captured. For consumers with fewer reviews ($M_c < M^*$), the closer M_c is to M^*, the more reliable their inferred preferences are considered to be. Consequently, the computation of price sensitivity coefficients Θ_s and quality sensitivity coefficients Φ_s for segment s is conducted as a weighted average, as follows:

$$\Theta_s = \frac{\sum_{c \in s} w_c * \hat{\theta}_c}{\sum_{c \in s} w_c} \quad (5)$$

$$\Phi_s = \frac{\sum_{c \in s} w_c * \hat{\phi}_c}{\sum_{c \in s} w_c} \quad (6)$$

4.2. Differential discount pricing strategy

Building on the consumer segmentation and the estimated price and quality sensitivity coefficients for each segment developed in the previous section, we consider a differential discount pricing strategy that maps the identified consumer segments to segment-specific prices.

From a theoretical standpoint, marketing history has proved that offering discounted prices, rather than just low prices, increases consumers' willingness to make a purchase (Armstrong & Chen, 2020; Gabler et al., 2017; Hsueh & Chen, 2010). From a practical perspective, many retailers have adopted the discounting price strategy, such as Tmall.com, JD.com and Amazon (Li et al., 2020). Therefore, we assume that the retailer differentiates pricing for various consumer segments by implementing distinct discounts, referred to as the differential discount pricing strategy, to maximise the total market profit. During the decision-making process, the retailer should first decide a fixed list price, p, based on their evaluation of the new product's quality within the category and achieve price differentiation for consumer segments by providing unique discounts, d_s, resulting in a price of $p_s = d_s * p$ for each consumer segment.

We consider a modified version of the multinomial logit (MNL) model, which integrates both price and quality sensitivity into consumer utilities. MNL has gained popularity in both theoretical and applied marketing studies as it identifies the predictors and value attributed to choice attributes in consumer decision-making, rooted in microeconomic utility theory (Nosrat et al., 2021). The utility derived by a consumer in segment s from purchasing the new product is as follows:

$$U_s = V_s + \epsilon_s \tag{7}$$

where V_s represents the expected utility, which remains consistent among consumers within segment s, while ϵ_s is a random variable that varies among consumers in segment s. As in the standard MNL model, $\epsilon_s, s \in S$ are independent Gumbel random variables. In our model, V_s of an individual consumer in segment s is determined by the quality of the product q and the differential price $d_s * p$, as follows:

$$V_s = \Phi_s * q - \Theta_s * d_s * p \tag{8}$$

In this model, each consumer makes a single purchase or chooses not to buy, which is indexed by $V_s^0 = 0$. The probability that an individual consumer in segment s buys the product reflects the proportion of consumers within segment s who make a purchase. To simplify matters, we normalise the total consumer population to 1, following the approach in studies like (Nosrat et al., 2021) and (Du et al., 2016). Thus, the size of segment s is denoted as $\gamma_s > 0$, where $\sum_s \gamma_s = 1$. Thus, by standard results for the MNL model, given the differential pricing strategy $[d_s * p | s \in S]$, the probability that a consumer in segment s makes a purchase is calculated in Equation 9.

$$\lambda_s = P(U_s > U_s^0) = \frac{e^{V_s}}{e^{V_s^0} + \sum_s e^{V_s}} \tag{9}$$

Thus, the retailer's differential discount pricing problem is formulated as follows:

$$\max \sum_{s \in S} d_s * p * \gamma_s * \lambda_s \tag{10}$$

$$s.t. = \begin{cases} d_{\min} \leq d_s \leq 1 & \forall s \in S \\ |d_s - d_{s'}| \leq \tau & \forall s, s' \in S \\ p_{\min} \leq p \leq p_{\max} & \end{cases} \tag{11}$$

The objective function of the optimisation problem is to maximise the total profit for the retailer across all consumer segments. Discount decisions are bound by specific constraints: the upper limit is set at 1, indicating that the retailer's pricing cannot surpass the predetermined list price. To maintain market stability, we also impose a lower limit on discounts to ensure they do not drop below $d_{\min}$. Furthermore, the list price, p, is subject to specific upper and lower constraints, which are related to the quality of the product, such as between 0.5 times and 1.5 times the quality. In addition, we introduce constraints on the degree of price differentiation, ensuring that the difference between any two market prices for the new product does not exceed τ.

What needs to be emphasised further is that, with the sales of the new product, reviews for products within this category will gradually increase. Therefore, in practical use, it is essential to update the parameters in the model based on the latest reviews. For consumers already in the market, if someone encounters new reviews in the current category, their credibility weighting factor, and even the price and quality sensitivities, will be updated accordingly based on the current review quantity and text. Simultaneously, as the product is sold, new consumers may enter the market. Similarly, we need to identify the price and quality sensitivity of these consumers in the same way as before and conduct the latest consumer segmentation and pricing for all current consumers in the market. Such an updating mechanism ensures that the retailer has a grasp of the potential consumer market characteristics for the product, enabling real-time adjustments to pricing strategies and maximising profits.

5. Experiments and case study

5.1. Experiments of consumer segmentation

In this section, we will experiment with the consumer segmentation method proposed in Section 3 using the Amazon dataset to validate the feasibility of the approach.

5.1.1. Experimental settings

To prepare data for this experiment, we extract review data for headphones from the Amazon dataset within the Electronics category. The number of review texts is approximately 50k, 26k, 29k, 49k, and 122k for rating scores from 1 to 5, respectively. For the review dataset, we employ $N = 10$ to divide the training dataset and input dataset (as depicted in Figure 2). The extracted input dataset contains 22 reviewers along with 364 reviews. These 22 reviewers will then undergo consumer segmentation in Section 5.1.3 based on the trained model in Section 5.1.2.

In our study, we employ the Transformer as our classifier due to its powerful capability in capturing contextual relationships. One of the most widely used pretraining systems is bidirectional encoder representations from transformers (BERT) (Devlin et al., 2018). It is shown that BERT and its variants have been fine-tuned for various sentiment classification problems (Gao et al., 2019; Hoang et al., 2019; Pota et al., 2020; Yin et al., 2023). In our paper, we use the implementation of the Bert-base-multilingual-cased from Hugging Face,[1] which consists of 12 layers, 12 attention heads, and a hidden size of 768. The model supports a maximum sequence length of 512 tokens.

Furthermore, we evaluate several commonly used pre-trained Transformer models, including BERT, BART, T5-small and T5-base, using implementations from the Hugging Face library. Compared to BERT-base-multilingual, BERT-base is an English-only model trained exclusively on English corpora, making it more specialised for English NLP tasks. BART-base follows a sequence-to-sequence architecture, leveraging denoising autoencoding pretraining to improve text generation and reconstruction tasks. T5-small and T5-base both treat every NLP task as a text-to-text transformation, enabling a unified approach to various language tasks. These models provide additional comparisons to assess how different Transformer-based architectures impact sentiment classification performance.

All the results shown in the following sections are the mean of experimental results from multiple runs (3–5 times). The reason for this is to avoid possible bias. Our approach is implemented in PyTorch.

Table 2. Accuracy of different matching solutions.

Matching solution			
Negative	Neutral	Positive	Prediction accuracy
(1, 2)	(3)	(4, 5)	**78.1**%
(1, 2)	(3, 4)	(5)	77.3%
(1)	(2, 3)	(4, 5)	76.6%

5.1.2. Experiments of DL-based sentiment classification

In this section, we use the training dataset to obtain the trained Transformer model for preparation for the consumer segmentation later. We create a dataset from the training dataset obtained in Section 5.1.1 to train the Transformer model, comprising a total of 40,000 reviews, with each label containing 8,000 reviews. The test dataset contains 1,000 review texts for each score, totalling 5,000.

To improve the training efficiency and improve classification accuracy, we first explore the mapping of rating scores from 1 to 5 onto the three labels "negative", "neutral", "positive". Following Liu et al. (2024), we investigate three possible combinations of matching solutions and the results are shown in Table 2.

Table 2 shows the prediction accuracy results of each matching solution, where the matching solution {*"negative": (1, 2), "neutral" (3), "positive": (4, 5)*} hasthe best result *78.1*%, which is higher than the other two and is in **bold**. Hence, we select this mapping solution to relabel the training dataset and then input the dataset into the Transformer model for training. After obtaining the trained model, we can classify and score the extracted price and quality review text, thereby further segmenting consumers, as discussed in Section 5.1.3.

As reviewed before, the current works of consumer segmentation and differential pricing often utilise traditional machine learning-based sentiment analysis, the unsatisfying prediction accuracy and, thus, inevitably affects segmentation results and further optimal decisions. Besides, we utilise two dimensions (price and quality) to segment the consumer and make the optimal pricing strategies, which are different from most of the current work. Based on these, we could say the good or bad of a differential pricing model depends on the consumer segmentation, which depends on the performance of the sentiment analysis model. To compare our method with others and demonstrate the advantages, we conducted a comparative analysis of the performance of the Transforms and ML methods.

We use the same data (under 1st matching solution) to train and test the ML classifiers. Grid Search is used to optimise the parameters of all ML classifiers. The results are shown in Table 3.

Table 3 shows that Transformer achieves the best performance in prediction accuracy (*85.88*%), and

Table 3. Test results for transformer and ML methods.

Classifier	Method	Test accuracy	Training times (mins)
Transformer (BERT-based)	DL	**85.88**%	62.66
XGBoost	ML	73.92%	64.58
Naive Bayes	ML	71.44%	24.51
KNN	ML	16.66%	171.2
SVM	ML	NA	NA
Gradient boosting	ML	68.32%	34.51
Stacking of XGB and NB	ML	75.80%	**14.12**

Table 4. Test results for different pre-trained transformer models.

Method	Test accuracy	GPU RAM	Parameters	Training times (mins)
BERT-base-multilingual-cased	**85.88%**	6.5	170 M	**62.66**
BERT-based-uncased	82.5%	5.9	110M	56.22
T5-small	78.56%	**5.2**	60M	**25.14**
T5-base	81.68%	11.1	**220M**	101.87
BART-base	82.02%	8.2	140M	300.31

Stacking of XGB and NB has the fastest training times (*14.12 mins*), both of which are in **bold**. Among all the tested methods, the Transformer model achieves the highest test accuracy at 85.88%, significantly outperforming traditional ML models such as XGBoost and Naïve Bayes. Even the stacking method, which combines XGBoost and Naïve Bayes, only reaches 75.80%, demonstrating that Transformers, capture complex patterns in text data more effectively than conventional ML approaches. Additionally, while Transformers require 62.66 min for training, this time is comparable to that of XGBoost and much lower than KNN, which performs poorly. It is worth noting that for all ML models, we conduct a grid search for hyperparameter tuning, which increases training time. However, in the stacking method, we directly use the best-selected parameters from XGBoost and Naïve Bayes without additional tuning, leading to a shorter training time.

Overall, the results indicate that the implementation cost of Transformers is manageable and justified by the improvement in accuracy. This reinforces the advantage of using DL models in sentiment classification, particularly when higher accuracy is essential for practical applications.

Furthermore, we further analyse the performance of different pre-trained Transformer models (BERT, T5, and BART) in the same task. All experiments are conducted on an NVIDIA A100 GPU. The results are presented in Table 4.

From Table 4, we can see the BERT-base-multilingual-casedmodel achieved the best test accuracy (*85.88%*), T5-small uses the lowest GPU RAM (*5.2 G*) and training times (*25.14 mins*), and T5-based has the most parameters (*220M*), all of which are in **bold**. In terms of test accuracy, our BERT-base-multilingual-cased model achieved 85.88%, outperforming other Transformer variants, demonstrating its strong classification ability in multilingual settings. The results suggest that T5 and BART, as generative models, are slightly less effective in classification tasks than BERT, which is specifically optimised for representation learning. Notably, the superior performance of the BERT-base-multilingual-cased model can be attributed to its ability to handle multilingual text more effectively. In online reviews, many users incorporate their native languages along with English, making it challenging for the English-only model (such as BERT-based-uncased) to capture sentiment accurately. We also consider computational efficiency. BERT-base models require relatively low GPU memory and shorter training times, making them more resource-efficient than encoder-decoder models like T5-base and BART-base. These generative models consume more memory and require significantly longer training times due to their architectural complexity.

Overall, BERT-base-multilingual-cased achieves a strong balance between accuracy, computational efficiency, and training time, making it well-suited for sentiment classification tasks. Additionally, our framework can seamlessly integrate different Transformer-based pre-trained models, enabling users to select the most suitable option based on their specific needs.

In summary, all the experiments in this section prove that the trained DL model in our approach has strong prior knowledge to perform sentiment classification for extracted feature texts without needing any further training. Compared to the existing ML-based models, our sentiment analysis model shows correctness, reasonability and advantages. This also proves that the segmentation strategies based on our model can provide a more accurate reflection of consumer characteristics compared to the existing studies.

5.1.3. Experiments of consumer segmentation

In this section, we employ the trained Transformer to derive the probability distribution across all labels and then get the consumers' price and quality sensitivities to conduct consumer segmentation.

First, we extract text features related to price and quality from the input dataset. According the Step 2 in Section 3.2, we first establish the price-related and quality-related vocabulary for the headphone

Table 5. Example results of the probability distributions of price and quality texts.

		Price-related			Quality-related			Original		
reviewerID	reviewTime	Neg	Neu	Pos	Neg	Neu	Pos	Neg	Neu	Pos
AIFLY2H F8NS8U	04 29,2012	0.19	0.95	0.16	0.27	0.65	0.08	0.40	0.56	0.04
AIFLY2H F8NS8U	02 9, 2013	0.04	0.59	0.37	0.01	0.31	0.68	0.08	0.91	0.11
				…						

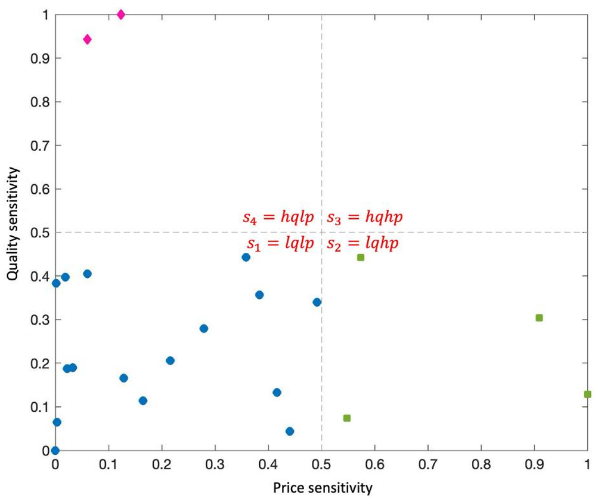

Figure 5. Consumer segmentations in the headphone market.

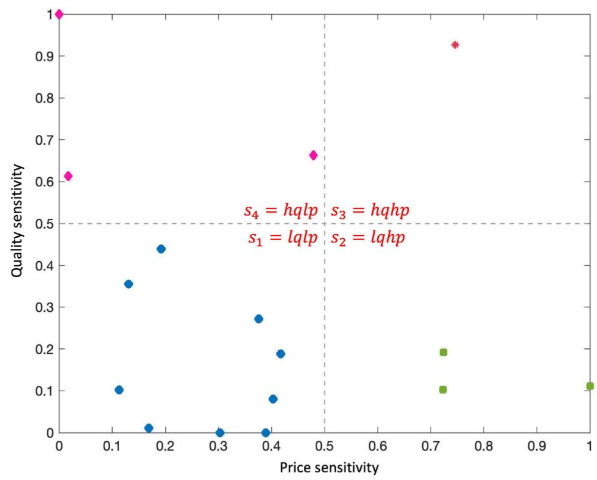

Figure 6. Consumer segmentations in the cream market.

market as shown in Table A4. We invite experts from Beihang University with an English language and literature study background to identify the most important feature words and eliminate irrelevant terms associated with the products. Specifically, the experts select and filter the most representative words from the high-frequency list to establish the vocabulary. A majority vote is implemented if they have different opinions on a feature word. Then, based on the vocabulary, we extract the feature texts, along with the original review text and input them into the trained Transformer classification model, resulting in probability distributions across all labels (refer to Table 5). Utilising the obtained probability distribution, we compute price and quality scores for each review using Equation (1). A basic linear fit is then employed within the model selection process to determine the parameters θ_c and ϕ_c. Finally, Equations (2) and (3) are applied for the normalisation of price and quality sensitivities, respectively, across all consumers.

After normalising the consumers' price and quality sensitivities, the result of consumer segmentations is presented in Figure 5. The axes of Figure 5 represent price sensitivity and quality sensitivity, and each consumer corresponds to a point within a specific coordinate region. Using 0.5 as the cut-off value on both dimensions, the region is divided into four sections, aligning with the consumer segments outlined in Section 4. From Figure 5, it can be observed that in the headphone market, the selected consumers are distributed across segments s_1, s_2, and s_4, with the highest proportion of consumers located in segment s_1. There is a significant variation in both price and quality among different products in the headphone market. For the majority of consumers, when purchasing headphones, as long as the headphones have basic functionality and are reasonably priced, it is sufficient. Therefore, s_1 occupies the majority of the market. As for the remaining consumers, a portion of them may have high-performance requirements for headphones, such as professionals in the music industry, distributed in the s_4 region. Another segment of consumers considers headphones as consumables, prioritising low prices with less emphasis on quality, distributed in the s_2 region. Due to the strong correlation between the quality of headphones and their cost, it is challenging to find products where price and quality are positively correlated. Consequently, it is difficult to find low-priced, high-quality products, which is why consumers in s_3 have not yet emerged.

Following the same process of consumer segmentation for the headphone market, we also conduct experiments in the cream market in the Luxury beauty category on Amazon and the result of the consumer segmentation in the cream market is shown in Figure 6. In the cream market, consumers are distributed across four segments, with a relatively higher concentration of consumers in the s_1 region. Cream can be considered a consumable in the skincare product category, and its effectiveness may not be entirely significant. Therefore, for the majority of consumers, price and quality are not highly sensitive factors. However, consumers in segment s_4, require high demands for skincare, they are very sensitive to the quality of the product but are not concerned about the price. On the contrary, some consumers only seek products with high cost-effectiveness, for example, in the s_2 region. Unlike the headphone market, the price and actual quality of the cream products are not entirely correlated. There is a certain brand premium in the pricing process of cream, so some consumers will conduct detailed comparisons before making a purchase, selecting products that satisfy both price and quality. However, the selection process may be relatively time-consuming, leading to a limited number of consumers in the s_3 region.

In summary, the results of the experiments in this section indicate that our proposed deep learning-based classification method is viable for consumer segmentation in a specific product market based on online review datasets. Different product markets exhibit distinct consumer segmentation characteristics. This offers retailers new methods and insights to effectively utilise online data for market analysis. Furthermore, from a consumer behaviour perspective, different groups display varying sensitivity to price and quality based on their shopping preferences and priorities. For instance, consumers in s_1 prioritise value for money, choosing products that are affordable while meeting their basic needs. In contrast, those in s_4 place greater emphasis on product performance, brand reputation, and long-term usability, leading them to prefer higher-quality options. Consumers in s_2, on the other hand, tend to be highly price-sensitive, opting for lower-cost, easily replaceable products rather than focusing on quality. Consumers in s_3, classified as high-quality, high-price segmentation, demonstrate a strong preference for premium products and are less concerned about price. They often associate higher prices with better quality and are willing to pay a premium for superior materials or exclusive features. This segment is typically composed of brand-loyal consumers, professionals, or luxury buyers, who view their purchases as long-term investments rather than short-term cost-saving decisions. These differences explain the distribution of consumers across segments and provide valuable guidance for retailers in refining pricing strategies, product selection, and marketing approaches.

5.2. Case study of the differential discount pricing policy

Building upon the consumer segmentation results mentioned above, this section focuses on optimising the differential discount pricing strategy for a new product. To illustrate, we will conduct a detailed exploration using the example of the headphone market.

5.2.1. Results of differential pricing strategy

As shown in Figure 5 above, the respective sizes of each segment in the headphone market are $\gamma_{s_1} = 0.73, \gamma_{s_2} = 0.18, \gamma_{s_3} = 0, \gamma_{s_4} = 0.09$. To calculate the average quality and price sensitivity coefficients for each segment, we set the credibility threshold M^* to be 20. Then, we assume the lower limit on discounts $d_{\min} = 0.5$, the upper and lower constraints of list price are $p_{\min} = 0.5q$ and $p_{\max} = 1.5q$. The degree of price differentiation τ is set to be 0.5. The quality q is set to be 10.

Table 6. Results of differential discount pricing strategy for the new headphone product.

	Differential discount price strategy				
List price	s_1	s_2	s_3	s_4	Uniform price
15	85%	50%	100%	100%	10

Based on the parameters' settings and assumptions above, we first obtain the differentiated discount pricing (DDP) strategy in the headphone market by solving the optimisation problem. Our problem is a constrained non-linear optimisation problem. After comparing various algorithms, we choose the Sequential Least-Squares Quadratic Programming (SLSQP) algorithm (Boggs & Tolle, 1995) to solve it. The fundamental principle of the SLSQP algorithm is rooted in the sequential optimisation approach and can handle diverse constraints, including inequalities, making it suitable for complex optimisation problems. Thus, our experiments are conducted in Python 3.9.6 using the solver "SLSQP" of the SciPy package for optimisation.

Meanwhile, for comparison purposes, we establish a uniform pricing (UP) model to serve as a benchmark. In this model, retailers do not segment consumers and apply a UP strategy to all consumers. Therefore, the price and quality sensitivity coefficients for consumers are the weighted averages of all consumers, calculated following the process consistent with Equations (5) and (6). The results of the DDP strategy and the UP strategy are shown in Table 6. Notably, for previously unencountered consumer segments, such as the s_3 segment in the headphone market, where we lack information about their price and quality sensitivities, we assume that retailers will directly utilise the list price without applying any discount. As shown in Table 6, the retailer exhibits differential discounts for different consumer segments. For consumers with lower price sensitivity, such as s_1 and s_4, the retailer tends to opt for higher prices to maximise marginal profits. Conversely, for price-sensitive consumers, such as s_2, the retailer is inclined to implement higher discounts to attract their consumption. What's more, in the current headphone market, given the very low proportion of consumers in the s_4 segment (only 0.09), the decision-making process may prioritise the main market strategy on larger consumer segments, such as s_1, while decisions for s_4 may align closely with those for s_1.

Table 7. Summary of revenue comparison between DDP and UP strategies.

Experiment	Differential discount price strategy	Uniform price strategy	Percentage difference
1	5457.90	4811.10	13.44%
2	5542.42	5044.91	9.86%
3	5208.47	5008.95	3.98%
4	5297.41	5085.81	4.16%
5	5367.84	4921.75	9.06%
6	5292.29	5024.89	5.32%
7	5131.20	4767.14	7.64%
8	5389.67	5019.25	7.38%
9	5138.98	4997.67	2.83%
10	5449.19	4891.33	11.41%
11	5123.45	5075.14	0.95%
12	5240.62	5080.14	3.16%
13	5424.70	4939.30	9.83%
14	5100.74	4821.89	5.78%
15	5202.77	5009.51	3.86%
16	4972.12	4819.57	3.17%
17	5263.97	5032.47	4.60%
18	5456.76	4941.54	10.43%
19	5506.07	4945.77	11.33%
20	5072.91	4910.10	3.32%

5.2.2. Value of differential discount pricing

To validate the efficacy of the DDP strategy, we conduct several simulation experiments to compare it against the UP strategy. Specifically, we conduct a total of 20 experiments, each involving 1000 random samplings from the interval $[0,1] * [0,1]$ for both price sensitivity and quality sensitivity. Each sampling can represent a consumer. In the DDP strategy, the retailer segments consumers and applies corresponding differential discount pricing. The total revenue was calculated based on 1000 samples (consumers). Similarly, in the UP strategy, the retailer sets the uniform price across all consumers and calculates the total revenue based on 1000 samples. The random seeds are fixed in each experiment so that both pricing strategies encounter the same consumers for a fair comparison. The results of all experiments are summarised in Table 7.

From Table 7, it is observed that the DDP strategy consistently outperforms the UP strategy in terms of revenue generation across all experiments. On average, the differential pricing strategy is approximately 7% higher revenue compared to the UP strategy. The largest revenue difference observed was 13.44%, while the smallest was 0.95%. These findings highlight the advantages of implementing a differential discount pricing strategy based on consumer segments, based on their price and quality sensitivities. By providing different discounts on the list price to different consumer segments, retailers can maximise revenue potential and enhance overall profitability. Moreover, the results emphasise the importance of consumer data and market segmentation to optimise pricing strategies and drive competitive advantage.

Furthermore, to validate the robustness of the results, we conduct 16 sets of experiments, varying the quality of the product from 5 to 20. For each quality value, we derive the optimal differential

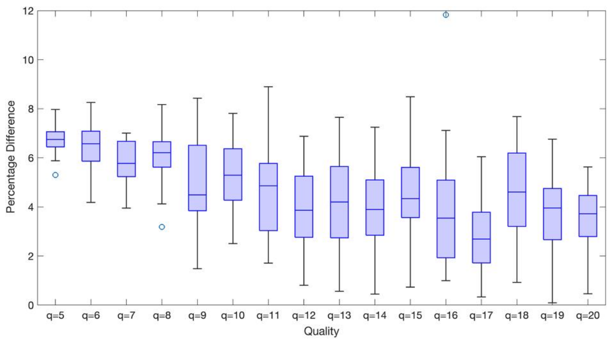

Figure 7. Percentage difference between differential discount pricing and uniform pricing across different qualities.

pricing strategy and uniform pricing strategy. Subsequently, for each q value, we conduct 16 sets of experiments, each containing 1000 samples. Figure 7 shows the percentage differences between the differential DDP strategy and the UP strategy under different quality settings. The consistent performance of the differential discount pricing strategy across various quality settings demonstrates its effectiveness in maximising retailers' revenue. From a managerial perspective, this result provides retailers with a stable framework for implementing a differential pricing strategy. Regardless of the quality of new products, retailers can utilise an appropriate differential discount pricing strategy to maximise their revenue.

5.3. Discussions

In this section, we initially conducted several experiments on the proposed approach of extracting consumers' price and quality sensitivities from online reviews collected from Amazon. The results of the experiments indicate that our method effectively achieves high-precision sentiment classification and segmentation of retailers along two dimensions: price and quality sensitivity. Next, based on the derived consumer segmentation and the characteristics of each segment, we determined the optimal differential discount pricing strategy for retailers. To validate the effectiveness of the strategy, we employed simulation experiments to compare the optimal profits obtained from the differential discount pricing strategy with those from the uniform pricing strategy. The experimental results demonstrate that differential pricing has a significantly positive impact on increasing retailers' profits. As mentioned at the end of Section 4, with the increasing number of product reviews, the characteristics and distribution of consumers in the market will also change. Therefore, the whole process of calculation (including DL-based sentiment classification and consumer segmentation) will periodically be redone to update the consumer segmentation database and pricing strategies, which allows the retailer to continuously maximise profits.

5.4. Discussion

In this section, we present experiments on consumer segmentation and the resulting differential pricing strategies. The simulation results show that, when consumers' price and quality sensitivities are accurately captured, differential pricing can substantially increase retailer profits compared with uniform pricing. One limitation of the strategy is that its effectiveness depends on the quality and quantity of online review data, with pricing being more precise for consumers who actively leave reviews. Nevertheless, as the number of product reviews grows over time, the entire process, including DL-based sentiment classification and consumer segmentation, can be iteratively updated to refresh the consumer segmentation database and pricing strategies, allowing the retailer to progressively improve pricing accuracy and continuously maximise profits.

6. Conclusion

In this paper, we investigate a differential pricing strategy with consumer segmentation based on online reviews. Unlike existing studies, we extracted consumer characteristics along two dimensions, price sensitivity and quality sensitivity, from online reviews and used them to segment consumers into four distinct groups for implementing differential pricing to maximise retailer profit. To extract these features, we employ a DL-based method to perform sentiment classification on raw reviews related to price and quality, thus improving the precision of our analysis. Simultaneously, consumer identification is no longer based on a single review but rather on all reviews from consumers within the current product category, further increasing the precision of consumer identification and segmentation.

Our research makes significant theoretical and practical contributions. Theoretical contributions include advancements in consumer preference analysis and differential pricing. While existing research primarily analyses consumer preferences regarding a specific product's features by his/her review (normally one review), our study expands this analysis by extracting consumer preferences for both price and quality from his/her historical online reviews of the products in the same category. Meanwhile, the experiment results demonstrate that the DL-based sentiment analysis method, particularly the BERT-based Transformer model, outperforms the traditional ML-based method and other pre-trained Transformer-based NLP models in our tasks. It achieves higher prediction accuracy, provides a more accurate reflection of consumer characteristics, and enables more precise segmentation. Therefore, we provide a novel comprehensive decision-making framework for consumer segmentation and differential pricing based on online reviews.

From a practical perspective, our study offers valuable management implications for retailers. Our decision-making framework could efficiently utilise online product reviews to do decision support for retailers: segment the consumers and propose more effective differential pricing strategies to maximise their profit. Moreover, our framework allows retailers to seamlessly integrate any Transformer-based NLP models based on their specific tasks and needs. The experiment results validate the feasibility and wide applicability of the proposed workflow across various product categories. Meanwhile, the experiment results also demonstrate that the proposed differential pricing strategy in our model has a significantly positive impact on increasing retailers' profits compared with the uniform pricing strategy, providing theoretical support for retailers to adopt differential pricing strategies. Therefore, in real-world business scenarios, retailers can apply our method to segment target consumers and identify the characteristics of consumers within each segment, assisting further decision-making. Furthermore, we provide several references and insights into retailers' differential pricing strategies. In our optimisation model, we integrate practical market rules by introducing constraints, such as differentiated limitations between various price discounts and constraints on the list price based on product quality. This enhances the practical applicability of the model, making it suitable for direct use by retailers in real-world scenarios. However, it is worth noting that although differential pricing can be profitable for retailers, this pricing strategy may also evoke negative emotions among consumers. Therefore, retailers need to take consumer attitudes into further consideration when implementing it.

As with any study, our study also has certain limitations and suggests directions for future research. Firstly, in the extraction of text related to price features, we utilised a method based on a pre-established vocabulary. While we expanded the content of the vocabulary as much as possible, there may still be some omissions. Secondly, in the segmentation of consumers, we employed a linear regression method to calculate consumer price and quality sensitivity. However, in real-world scenarios, factors influencing overall satisfaction and their relationships may be more complex. Given the outcomes of this study and the limitations above, we propose several avenues for further research. Firstly, in identifying consumer price and quality sensitivity, considering additional influencing factors and more complex relationship models could enhance the accuracy of consumer identification. Secondly, the decision-making for differential pricing can evolve into more dynamic decisions, allowing retailers to implement real-time differential pricing based on the unique characteristics of each consumer, potentially maximising profits.

Note

[1]https://huggingface.co/models

Acknowledgements

The authors would like to thank Prof Martin Kunc from the University of Southampton for his conscientious and constructive comments on this paper. The work is supported by the National Natural Science Foundation of China (No. 72301060, 72171008). Dr Liwei Xu is supported by the Key Projects of the Liaoning Provincial Social Science Fund (No. L25AXW001).

Disclosure statement

No potential conflict of interest was reported by the authors.

Data availability statement

The original raw data used in this study are openly available at https://nijianmo.github.io/amazon/index.html (Ni et al., 2019). The experimental data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Ahani, A., Nilashi, M., Yadegaridehkordi, E., Sanzogni, L., Tarik, A. R., Knox, K., Samad, S., & Ibrahim, O. (2019). Revealing customers' satisfaction and preferences through online review analysis: The case of Canary Islands hotels. *Journal of Retailing and Consumer Services*, *51*, 331–343. https://doi.org/10.1016/j.jretconser.2019.06.014

Akaike, H. (1987). Factor analysis and aic. *Psychometrika*, *52*(3), 317–332. https://doi.org/10.1007/bf02294359

Armstrong, M., & Chen, Y. (2020). Discount pricing. *Economic Inquiry*, *58*(4), 1614–1627. https://doi.org/10.1111/ecin.12774

Ban, G.-Y., & Keskin, N. B. (2021). Personalized dynamic pricing with machine learning: High-dimensional features and heterogeneous elasticity. *Management Science*, *67*(9), 5549–5568. https://doi.org/10.1287/mnsc.2020.3680

Bi, J.-W., Liu, Y., Fan, Z.-P., & Cambria, E. (2019). Modelling customer satisfaction from online reviews using ensemble neural network and effect-based Kano model. *International Journal of Production Research*, *57*(22), 7068–7088. https://doi.org/10.1080/00207543.2019.1574989

Boggs, P. T., & Tolle, J. W. (1995). Sequential quadratic programming. *Acta Numerica*, *4*, 1–51. https://doi.org/10.1017/s0962492900002518

Bonatti, A., & Cisternas, G. (2020). Consumer scores and price discrimination. *The Review of Economic Studies*, *87*(2), 750–791. https://doi.org/10.1093/restud/rdz046

Cai, J., Li, J., Li, W., & Wang, J. (2018). *Deeplearning model used in text classification* [Paper presentation].2018 15th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), in, IEEE, pp. 123–126.

Cai, X., Li, J., Dai, B., & Zhou, T. (2018). Pricing strategies in a supply chain with multi-manufacturer and a common retailer under online reviews. *Journal of Systems Science and Systems Engineering*, *27*(4), 435–457. https://doi.org/10.1007/s11518-018-5380-x

Cavanaugh, J. E., & Neath, A. A. (2019). The Akaike information criterion: Background, derivation, properties, application, interpretation, and refinements. *WIREs Computational Statistics*, *11*(3), e1460. https://doi.org/10.1002/wics.1460

Chaerudin, S. M., & Syafarudin, A. (2021). The effect of product quality, service quality, price on product purchasing decisions on consumer satisfaction. *Ilomata International Journal of Tax and Accounting*, *2*(1), 61–70. https://doi.org/10.52728/ijtc.v2i1.202

Chong, A. Y. L., Ch'ng, E., Liu, M. J., & Li, B. (2017). Predicting consumer product demands via big data: The roles of online promotional marketing and online reviews. *International Journal of Production Research*, *55*(17), 5142–5156. https://doi.org/10.1080/00207543.2015.1066519

Colombo, S. (2018). Behavior- and characteristic-based price discrimination. *Journal of Economics & Management Strategy*, *27*(2), 237–250. https://doi.org/10.1111/jems.12244

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). Bert: Pre-training of deep bidirectional transformers for language understanding. *In Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies*, *1*, 4171-4186. https://doi.org/10.18653/v1/N19-1423

Ding, J., Tarokh, V., & Yang, Y. (2018). Model selection techniques: An overview. *IEEE Signal Processing Magazine*, *35*(6), 16–34. https://doi.org/10.1109/msp.2018.2867638

Du, C., Cooper, W. L., & Wang, Z. (2016). Optimal Pricing for a Multinomial Logit Choice Model with Network Effects. *Operations Research*, *64*(2), 441–455. https://doi.org/10.1287/opre.2016.1487

Duan, Y., Liu, T., & Mao, Z. (2022). How online reviews and coupons affect sales and pricing: An empirical study based on e-commerce platform. *Journal of Retailing and Consumer Services*, *65*, 102846. https://doi.org/10.1016/j.jretconser.2021.102846

Feng, J., Li, X., & Zhang, X. (. (2019). Online product reviews-triggered dynamic pricing: Theory and evidence. *Information Systems Research*, *30*(4), 1107–1123. https://doi.org/10.1287/isre.2019.0852

Fu, X., Chen, X., Shi, Y.-T., Bose, I., & Cai, S. (2017). User segmentation for retention management in online social games. *Decision Support Systems*, *101*, 51–68. https://doi.org/10.1016/j.dss.2017.05.015

Fu, Y., Gu, B., Xie, Y., Ye, J., & Cao, B. (2021). Channel structure and differential pricing strategies in dual-channel e-retail considering e-platform business models. *IMA Journal of Management Mathematics*, *32*(1), 91–114. https://doi.org/10.1093/imaman/dpaa015

Fudenberg, D., & Villas-Boas, J. M. (2006). Behavior-based price discrimination and customer recognition. *Handbook on economics and information systems*. *1*, 377–436.

Gabler, C. B., Myles Landers, V., & Reynolds, K. E. (2017). Purchase decision regret: Negative consequences of the Steadily Increasing Discount strategy. *Journal of Business Research*, *76*, 201–208. https://doi.org/10.1016/j.jbusres.2017.01.002

Gao, J., Peng, P., Lu, F., Claramunt, C., Qiu, P., & Xu, Y. (2024). Mining tourist preferences and decision support via tourism-oriented knowledge graph. *Information Processing & Management*, *61*(1), 103523. https://doi.org/10.1016/j.ipm.2023.103523

Gao, Z., Feng, A., Song, X., & Wu, X. (2019). Target-dependent sentiment classification with BERT. *IEEE Access*, *7*, 154290–154299. https://doi.org/10.1109/access.2019.2946594

Geladi, P., & Kowalski, B. R. (1986). Partial least-squares regression: A tutorial. *Analytica Chimica Acta*, *185*, 1–17. https://doi.org/10.1016/0003-2670(86)80028-9

Ghali-Zinoubi, Z., & Toukabri, M. (2019). The antecedents of the consumer purchase intention: Sensitivity to price and involvement in organic product: Moderating role of product regional identity. *Trends in Food Science & Technology*, *90*, 175–179. https://doi.org/10.1016/j.tifs.2019.02.028

Guo, Q., Chen, Y.-J., & Huang, W. (2022). Dynamic pricing of new experience products with dual-channel social learning and online review manipulations. *Omega*, *109*, 102592. https://doi.org/10.1016/j.omega.2022.102592

Han, S., Gupta, S., & Lehmann, D. R. (2001). Consumer price sensitivity and price thresholds. *Journal of Retailing*, *77*(4), 435–456.

Hoang, M., Bihorac, O. A., Rouces, J. (2019). Aspect-based sentiment analysis using Bert. In "*Proceedings of the 22nd Nordic Conference on Computational Linguistics*", pp. 187–196.

Hsueh, S.-C., & Chen, J.-M. (2010). Sharing secure m-coupons for peer-generated targeting via eWOM communications. *Electronic Commerce Research and Applications*, *9*(4), 283–293. https://doi.org/10.1016/j.elerap.2010.01.002

Jing, B. (2017). Behavior-based pricing, production efficiency, and quality differentiation. *Management Science*, *63*(7), 2365–2376. https://doi.org/10.1287/mnsc.2016.2463

Joung, J., & Kim, H. (2023). Interpretable machine learning-based approach for customer segmentation for new product development from online product reviews. *International Journal of Information Management*, *70*, 102641. https://doi.org/10.1016/j.ijinfomgt.2023.102641

Kostyra, D. S., Reiner, J., Natter, M., & Klapper, D. (2016). Decomposing the effects of online customer reviews on brand, price, and product attributes. *International Journal of Research in Marketing*, *33*(1), 11–26. https://doi.org/10.1016/j.ijresmar.2014.12.004

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Li, C., Chu, M., Zhou, C., & Zhao, L. (2020). Two-period discount pricing strategies for an e-commerce platform with strategic consumers. *Computers & Industrial Engineering*, *147*, 106640. https://doi.org/10.1016/j.cie.2020.106640

Li, J., Ji, X., & Perera, S. C. (2024). Behaviour-based pricing for multi-version information goods. *International Journal of Production Research*, *62*(14), 5185–5210. https://doi.org/10.1080/00207543.2023.2289073

Li, X., Ma, L., Lu, B., & Huang, K. (2023). Sincere or falsehearted? investigation of online reviews and merchant response. *International Journal of Electronic Commerce*, *27*(2), 185–209. https://doi.org/10.1080/10864415.2023.2184238

Liang, D., Dai, Z., Wang, M., & Li, J. (2020). Web celebrity shop assessment and improvement based on online review with probabilistic linguistic term sets by using sentiment analysis and fuzzy cognitive map. *Fuzzy Optimization and Decision Making*, *19*(4), 561–586. https://doi.org/10.1007/s10700-020-09327-8

Lii, Y-s., & Sy, E. (2009). Internet differential pricing: Effects on consumer price perception, emotions, and behavioral responses. *Computers in Human Behavior*, *25*(3), 770–777. https://doi.org/10.1016/j.chb.2009.02.005

Lin, C.-Y. (2004). ROUGE: A package for automatic evaluation of summaries. In Text summarization branches out, pp. 74–81.

Liu, H., Huang, Y., Wang, Z., Liu, K., Hu, X., & Wang, W. (2019). Personality or value: A comparative study of psychographic segmentation based on an online review enhanced recommender system. *Applied Sciences*, *9*(10), 1992. https://doi.org/10.3390/app9101992

Liu, Y., Shi, J., Huang, F., Hou, J., & Zhang, C. (2024). Unveiling consumer preferences in automotive reviews through aspect-based opinion generation. *Journal of Retailing and Consumer Services*, *77*, 103605. https://doi.org/10.1016/j.jretconser.2023.103605

Liu, Z., Liao, H., Li, M., Yang, Q., & Meng, F. (2024). A deep learning-based sentiment analysis approach for online product ranking with probabilistic linguistic term sets. *IEEE Transactions on Engineering Management*, *71*, 6677–6694. https://doi.org/10.1109/TEM.2023.3271597

McDonald, G. C. (2009). Ridge regression. *WIREs Computational Statistics*, *1*(1), 93–100. https://doi.org/10.1002/wics.14

Ng, C. Y., & Law, K. M. (2020). Investigating consumer preferences on product designs by analyzing opinions from social networks using evidential reasoning. *Computers & Industrial Engineering*, *139*, 106180. https://doi.org/10.1016/j.cie.2019.106180

Ni, J., Li, J., & McAuley, J. (2019). *Justifying Recommendations using Distantly-Labeled Reviews and Fine-Grained Aspects* [Paper presentation]. Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), Hong Kong, China. Association for Computational Linguistics pp. 188–197.

Nosrat, F., Cooper, W. L., & Wang, Z. (2021). Pricing for a product with network effects and mixed logit demand. *Naval Research Logistics (NRL)*, *68*(2), 159–182. https://doi.org/10.1002/nav.21943

Ogutu, J. O., Schulz-Streeck, T., Piepho, H.-P. (2012). Genomic selection using regularized linear regression models: Ridge regression, lasso, elastic net and their extensions. "*BMC Proceedings*", Vol. 6, Springer, pp. 1–6. https://doi.org/10.1186/1753-6561-6-S2-S10

Pandey, S., Pandey, N., & Chawla, D. (2023). Market segmentation based on customer experience dimensions extracted from online reviews using data mining. *Journal of Consumer Marketing*, *40*(7), 854–868. https://doi.org/10.1108/jcm-10-2022-5654

Park, J. (2023). Combined text-mining/DEA method for measuring level of customer satisfaction from online reviews. *Expert Systems with Applications*, *232*, 120767. https://doi.org/10.1016/j.eswa.2023.120767

Pota, M., Ventura, M., Catelli, R., & Esposito, M. (2020). An effective BERT-based pipeline for Twitter sentiment analysis: A case study in Italian. *Sensors*, *21*(1), 133. https://doi.org/10.3390/s21010133

Qin, J., Zeng, M., Wei, X., & Pedrycz, W. (2024). Ranking products through online reviews: A novel data-driven method based on interval type-2 fuzzy sets and sentiment analysis. *Journal of the Operational Research Society*, *75*(5), 860–873. https://doi.org/10.1080/01605682.2023.2215823

Ranstam, J., & Cook, J. A. (2018). Lasso regression. *British Journal of Surgery*, *105*(10), 1348–1348. https://doi.org/10.1002/bjs.10895

Raza, S. A. (2015). An integrated approach to price differentiation and inventory decisions with demand leakage. *International Journal of Production Economics*, *164*, 105–117. https://doi.org/10.1016/j.ijpe.2014.12.020

Saranya, C., & Manikandan, G. (2013). A study on normalization techniques for privacy preserving data mining. *International Journal of Engineering and Technology (IJET)*, *5*(3), 2701–2704.

Shin, D., Vaccari, S., & Zeevi, A. (2023). Dynamic pricing with online reviews. *Management Science*, *69*(2), 824–845. https://doi.org/10.1287/mnsc.2022.4387

Teimoury, E., Modarres, M., & Neishaboori, M. (2020). Cost-based differential pricing for a make-to-order production system in a competitive segmented market. *Journal of Revenue and Pricing Management*, *19*(4), 266–275. https://doi.org/10.1057/s41272-019-00211-8

Van Rijsbergen, C. J., Robertson, S. E., & Porter, M. F. (1980). *New models in probabilistic information retrieval*. Vol. 5587. British Library Research and Development Department London.

Varian, H. R. (1989). Price discrimination. *Handbook of Industrial Organization*, *1*, 597–654.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems. 30.

Wang, L., Han, M., Li, X., Zhang, N., & Cheng, H. (2021). Review of classification methods on unbalanced data sets. *IEEE Access*, *9*, 64606–64628. https://doi.org/10.1109/access.2021.3074243

Wang, X., & Ng, C. T. (2020). New retail versus traditional retail in e-commerce: Channel establishment, price competition, and consumer recognition. *Annals of Operations Research*, *291*(1-2), 921–937. https://doi.org/10.1007/s10479-018-2994-9

Wang, Y., Li, M., Feng, H., & Feng, N. (2023). Which is better for competing firms with quality increasing: Behavior-based price discrimination or uniform pricing? *Omega*, *118*, 102870. https://doi.org/10.1016/j.omega.2023.102870

Wind, Y., & Cardozo, R. N. (1974). Industrial market segmentation. *Industrial Marketing Management*, *3*(3), 153–165. https://doi.org/10.1016/0019-8501(74)90025-x

Wu, C., Bi, W., & Liu, H. (2023). Proximal policy optimization algorithm for dynamic pricing with online reviews. *Expert Systems with Applications*, *213*, 119191. https://doi.org/10.1016/j.eswa.2022.119191

Wu, P., Tang, T., Zhou, L., & Martínez, L. (2024). A decision-support model through online reviews: Consumer preference analysis and product ranking. *Information Processing & Management*, *61*(4), 103728. https://doi.org/10.1016/j.ipm.2024.103728

Wu, X., & Liao, H. (2021). Modeling personalized cognition of customers in online shopping. *Omega*, *104*, 102471. https://doi.org/10.1016/j.omega.2021.102471

Xiao, S., Wei, C.-P., & Dong, M. (2016). Crowd intelligence: Analyzing online product reviews for preference measurement. *Information & Management*, *53*(2), 169–182. https://doi.org/10.1016/j.im.2015.09.010

Xu, M., Bao, W., & Yang, D. (2025). Behavior-based pricing and wholesale contracting in competing supply chains with informative advertising. *Journal of the Operational Research Society*, *76*(6), 1140–1155. https://doi.org/10.1080/01605682.2024.2415129

Yan, X., & Han, X. (2022). Optimal pricing and remanufacturing entry strategies of manufacturers in the presence of online reviews. *Annals of Operations Research*, *316*(1), 59–92. https://doi.org/10.1007/s10479-021-04030-2

Yang, N., & Zhang, R. (2022). Dynamic pricing and inventory management in the presence of online reviews. *Production and Operations Management*, *31*(8), 3180–3197. https://doi.org/10.1111/poms.13744

Yang, W., Zhang, J., & Yan, H. (2021). Impacts of online consumer reviews on a dual-channel supply chain. *Omega*, *101*, 102266. https://doi.org/10.1016/j.omega.2020.102266

Yelkur, R., & DaCosta, M. M. N. (2001). Differential pricing and segmentation on the Internet: The case of hotels. *Management Decision*, *39*(4), 252–262. https://doi.org/10.1108/00251740110391411

Yin, S., Wang, Y., & Shafiee, S. (2023). Ranking products through online reviews considering the mass assignment of features based on Bert and q-rung orthopair fuzzy set theory. *Expert Systems with Applications*, *213*, 119142. https://doi.org/10.1016/j.eswa.2022.119142

Yu, Y., Yang, Y., Huang, J., & Tan, Y. (2023). Unifying algorithmic and theoretical perspectives: Emotions in online reviews and sales. *MIS Quarterly*, *47*(1), 127–160. https://doi.org/10.25300/MISQ/2022/16600

Zhang, Y., Yang, R., Yi, Z., Yao, S., & Jing, Y. (2023). Behavior-based pricing under asymmetric channel competition with strategic consumers. *Omega*, *120*, 102916. https://doi.org/10.1016/j.omega.2023.102916

Zhang, Y., Zhao, C., & Liang, Z. (2021). Frills and product pricing with online reviews. *Computers & Industrial Engineering*, *159*, 107461. https://doi.org/10.1016/j.cie.2021.107461
Zhao, C., & Peng, X. (2023). Influence of online reviews on the dynamics of product quality and pricing in a competitive market. *International Journal of Electronic Commerce*, *27*(3), 324–353. https://doi.org/10.1080/10864415.2023.2226899
Zhao, C., Wang, X., Xiao, Y., & Sheng, J. (2022). Effects of online reviews and competition on quality and pricing strategies. *Production and Operations Management*, *31*(10), 3840–3858. https://doi.org/10.1111/poms.13791
Zhao, C., & Zhang, Y. (2019). Dynamic quality and pricing decisions in customer-intensive service systems with online reviews. *International Journal of Production Research*, *57*(18), 5725–5748. https://doi.org/10.1080/00207543.2018.1543972
Zheng, J., Li, M.-Y., Yuan, D.-N., & Xie, S. (2025). Product ranking considering differences across online review platforms: A method based on intuitionistic fuzzy soft sets. *Journal of the Operational Research Society*, *76*(6), 1252–1275. https://doi.org/10.1080/01605682.2024.2417727
Zhou, J., Zhao, R., & Wang, B. (2020). Behavior-based price discrimination in a dual-channel supply chain with retailer's information disclosure. *Electronic Commerce Research and Applications*, *39*, 100916. https://doi.org/10.1016/j.elerap.2019.100916

Appendix A

Table A1. Example results of extracted sentence list.

Asin	ReviewerID	ReviewTime	Price-related text	Quality-related text
B00 MWR R8OA	AZKR FNQ8E FO4T	03 2, 2015	Again, at this price point, it should not be a surprise; it should be expected, and these hold up very well.	Sound Quality: Obviously, this is the most important quality, and once again, I came away very impressed.
B00 RSU FT5G	AIFL Y2HF 8NS8U	01 26, 2015	I think the current price (of this written review) of $100 is a bit steep, I would hesitate to recommend this if you see Amazon's fluctuating price drops this to $75	5 h on a single battery charge
…	…	…	…	…

Table A2. Sample review data structure.

Attribute	Value
overall	5.0
verified	True
reviewTime	07 27,2017
reviewerID	AUBO8VVMMPGZ2
asin	B00GYD782A
reviewerName	Bora Cobanoglu
reviewText	Been a zerolemon loyal customer and it all started with this phone and battery. I remember getting 12 h Screen on Time with this beast. If you currently have a s3 and want a powerful battery purchase this.
summary	Beast
unixReviewTime	1501113600

Table A3. Sample metadata structure.

Attribute	Value
asin	B01BWZ0WAY
title	Straight Talk Alcatel A521L One Touch Pop Star Prepaid Android Smartphone Phone
feature	["STORAGE: Internal Memory 4GB + 1GB RAM", … , "SPEED: 4 G LTE/Wi-Fi", "CAMERA: 5MP Camera"]
description	COMFORTABLY COMPACT 4 G LTE. … Your phone also comes ready to rock right out of the box, with all of your favourite apps preloaded.
also_buy	B0153UYDNG
also_viewed	["B077PYG9X9", "B077GZBNPP", … , "B00642EWMU"]
rank	"#729,240 in Cell Phones & Accessories (See Top 100 in Cell Phones & Accessories)", "#1,912 in Cell Phones & Accessories > Carrier Cell Phones"
brand	Straight Talk
categories	["Cell Phones & Accessories", "Cell Phones", "Carrier Cell Phones"]

Table A4. Price-related and quality-related vocabulary for the headphone market.

Price vocabulary		Quality vocabulary	
cost	expensive	quality	comfort
price	affordable	sound	expensive
expense	competitive	price	volume
value	high-priced	function	music
bargain	discounted	battery	button
discount	inexpensive	video	control
budget	overpriced	bass	
investment	economical		
affordability	costly		
payment	profitable		
inflation	budget-friendly		
profit			